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Do carbon emissions affect the cost of capital? Primary versus secondary corporate bond markets *

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Abstract

We empirically study whether carbon emissions affect US firms' cost of capital. We show that firms with higher carbon emissions tend to face higher cost of capital on the primary market. However, this carbon premium represents less than 15% of the one prevailing on the secondary market. A simple model attributes this gap to uncertainty about future climate preferences of investors and limited competition among primary market dealers. We find evidence for these two channels. Our findings imply that market imperfections reduce the effectiveness of the cost of capital channel in inducing firms to reduce their carbon emissions.

JEL classification: G12, G41

Keywords: Climate finance, Carbon premium, Bond markets, Green investors, Underwriting dealers

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1 Introduction

The corporate sector is the largest source of carbon dioxide (CO_2) and other greenhouse gases emissions (CDP, 2017). To limit global warming, the Intergovernmental Panel on Climate Change recommends net zero carbon emissions by 2050 (IPCC, 2021). However, there is currently no international tax or regulation of carbon emissions to align corporate and societal interests. Financial markets can fill part of this gap by requiring a larger expected return from brown firms, i.e., by imposing a carbon premium on firms with large carbon emissions.[1] This premium would imply a higher cost of capital for brown firms than for green firms.[2]

Several recent papers document a carbon premium in secondary equity markets. In their seminal analysis, Bolton and Kacperczyk (2021) find that US firms with larger absolute emissions display higher realized stock returns. Extending their analysis to stock markets around the world, they find that the carbon premium arises for all sectors and almost all countries in their sample (Bolton and Kacperczyk, 2023b). The presence of a carbon premium on secondary equity markets is questioned by Aswani, Raghunandan, and Rajgopal (2023a) and Zhang (2023).[3] However, using implied cost of capital as a proxy for expected returns, Chava (2014) and Pastor, Stambaugh, and Taylor (2022) also find higher stock returns for firms with lower environmental performances.

[1] In the present paper, we are agnostic as to why a carbon premium arises on financial markets. It may be due to social norms or reputation issues (see, e.g., Riedl and Smeets (2017)) that we summarize as tastes following Fama and French (2007), but it may also be due to climate-related physical and transition risk (see, e.g., Pankratz and Schiller (ming) and Seltzer, Starks, and Zhu (2022)). We summarize all these different motives for favoring green assets with low carbon emissions under the umbrella term of green preferences, keeping in mind that these preferences can refer to both tastes and beliefs regarding risk.

[2] See, e.g., the theoretical analysis of Pedersen (2023). For recent review papers on climate finance, see Hong, Karolyi, and Scheinkman (2020) and Giglio, Kelly, and Stroebel (2021), and on sustainable finance, see Edmans and Kacperczyk (2022).

[3] Aswani et al. (2023a) point to a bias in carbon emissions estimated by the data vendor. Abstracting from estimated emissions, they find no link between absolute carbon emissions and stock returns in the US market. Moreover, when using carbon intensity, the ratio of carbon emissions to revenues, instead of absolute carbon emissions, they find no carbon premium. Zhang (2023) points to a potential look-ahead bias due to lags in the disclosure of carbon emissions data. After accounting for this lag, Zhang (2023) does not find a carbon premium in global stock markets including the US. See also, (Bolton and Kacperczyk, 2023a) and (Aswani, Raghunandan, and Rajgopal, 2023b).

We shed new light on these issues by studying whether carbon emissions affect firms' cost of capital raised on bond markets. We focus on US corporate bond markets from 2005 to 2022 to examine the existence and magnitude of a carbon premium for corporate bonds, both on the primary and the secondary markets. The primary market, on which firms issue new financial assets, is the only point at which firms with low (high) carbon emissions can benefit from (be penalized with) a lower (higher) cost of capital if investors have a preference for green over brown projects. However, the allocation and pricing of corporate bonds on the primary market is not determined by an auction, as in the case of treasuries, but by underwriting dealers who act as intermediaries between issuing firms and investors, similar to the standard practice for Initial Public Offerings (IPO) on equity markets (Bessembinder, Spatt, and Venkataraman, 2020). This raises the question of whether the financial intermediaries pass on the carbon premium that they can anticipate on the secondary market to the issuing firms on the primary market. To address this question, we measure the carbon premium on the primary bond market and compare it to the carbon premium on the secondary market.

We focus on the corporate bond market for three reasons. First, bonds are an important source of financing for firms. According to the SIFMA (2023), US bond issuance in 2022 amounted to $1,356 billion versus $160 billion for the US equity markets. Second, this focus enables us to study primary markets to offer new evidence on an important issue, mostly studied for secondary equity markets. Third, it is relatively easier to estimate the expected returns required by investors to hold financial assets for bonds, that have fixed-income characteristics, than for equity, for which future potential cash flows are not predetermined.[4]

Using a sample of bonds issued by 219 US firms active on the market from 2005 to 2022, we establish our main result in three steps.[5] We measure the carbon premium as the (positive)

[4]Credit risk and liquidity issues may be an important concern and are addressed in our empirical methodology, presented below.

[5]In robustness checks, we apply less filter in constructing our sample and are able to run our cross-section analysis on bonds issued by 355 firms. We also conduct a time-series analysis on bonds issued by 302 firms. Our results hold in these extended samples.

sensitivity of corporate bond spreads to the carbon intensity of the issuing firms. First, we find that the carbon premium on the primary market is positive yet small in magnitude and that its statistical significance does not survive some of the robustness checks. Second, we document the existence of a carbon premium on secondary bond markets. This is a novel result.[6] Third, and more importantly, we show that the carbon premium is lower on the primary market than on the secondary market.

Our main specification features a cross-sectional analysis: for a given firm at a given bond issuance date, we compare the carbon premium on the bond issued on the primary market to the carbon premium on the secondary market, i.e., for bond(s) that were issued by the same firm at a previous date and that are trading on the same day.[7] Our estimates indicate that around 85% of the carbon premium that could be achieved on the secondary market is missing on the primary market. This leaves low-emission firms with only around 15% of the potential decrease in the cost of capital they could get if the carbon premium was as large on the primary as on the secondary market.

Indeed, on the primary market, we estimate a difference in yield of 2.4 basis points between green and brown firms, i.e., firms with Scope 1, 2, and 3 carbon intensity one standard deviation below and above average, respectively. On the secondary market, the difference in yield between green and brown firms is around 17 basis points. According to our analyses, the carbon premium appears stronger and more statistically robust on the secondary than on the primary bond market. We estimate that green firms missed, in 2022, $2.6 billion in issuance revenues compared to what they could have raised if the carbon premium had been as large on the primary

[6] The presence of a carbon premium on bond markets echoes findings in the experimental finance literature suggesting that subjects in investment situations are willing to sacrifice some expected returns in exchange for a responsible firm's conduct, see, Riedl and Smeets (2017); Bonnefon, Landier, Sastry, and Thesmar (2022); Brodback, Guenster, Pouget, and Wang (2022); Humphrey, Kogan, Sagi, and Starks (2022). These papers link the premium phenomenon to pro-social tastes or social norms. As already mentioned, we do not take a stance regarding the origin of the carbon premium that could be driven by taste or risk considerations.

[7] We show that our main result is robust to matching primary market bonds to the secondary market prices of only the most recently issued bond as of the primary market bond issuance.

as on the secondary bond market.[8]

We offer various additional analyses. We illustrate our main results with a time-series analysis that follows carbon premium evolution over time from the bond issuance on the primary market to trading on the secondary market. Moreover, we show that our results hold when we control for shocks to climate concerns (Ardia, Bluteau, Boudt, and Inghelbrecht, 2022), when we focus on investment-grade bonds, when we differentiate between brown and green firms based on average carbon intensity at the industry level. Our main result hold when we split our time period in two sub-samples, 2005-2013 and 2014-2022 or odd versus even years: although the existence of a carbon premium on the primary market appears less robust, we find a statistically significant and larger carbon premium on the secondary market in all time subsamples. Our results also hold when we consider absolute emissions instead of carbon intensity (Bolton and Kacperczyk, 2021), when we use more precise measures of carbon emissions (Aswani et al., 2023a), when we use an additional lag for data on carbon emissions (Zhang, 2023), and when we use different liquidity measures and winsorization levels.

We develop a simple theoretical model to explain our main results. The model considers underwriting dealers and segmented markets: buy-and-hold investors on the primary market have larger climate concerns than the ones on the secondary market. Absent market frictions, the carbon premium is the same on both markets. However, when dealers are risk averse and face uncertainty about investors' future climate preferences that they cannot diversify away, they demand a higher risk premium on the primary market. The carbon premium is thus reduced on the primary market relative to the secondary market. Similarly, with limited competition between

[8]This number, \$2.6 billion, comes from the following back-of-the-envelop computations. We consider that green firms have issued bonds for \$203.4 billion in 2022 (\$1,356 billion, i.e., total bond amount issued in 2022, times 0.15, i.e., top 15% of firms in terms of carbon efficiency, corresponding to the percentage of observations more than one standard deviation above the mean for normal distributions, our definition of green firms). We assume that this amount comes from the issuance of bonds with a yield of 3%, 10 years to maturity and a coupon rate of 3%. We then compute what would have been the amount obtained at issuance if bonds had instead a yield that is lower by 14.6 basis points, i.e., the difference between the yield of a top 15% firm in terms of carbon efficiency on the secondary and on the primary market: this amount would have been \$206 billion and is \$2.6 billion larger than what has actually been obtained by green firms.

dealers, the carbon premium that exists in the secondary market is not fully transmitted to the primary market.

We find evidence in favor of these two economic effects. We measure uncertainty in investors' future climate change concerns by applying an ARCH model to the Media Climate Change Concerns index of Ardia et al. (2022). The presence of this uncertainty channel echoes the empirical findings of Avramov, Cheng, Lioui, and Tarelli (2022) on ESG ratings uncertainty and Pastor, Stambaugh, and Taylor (2022) on demand shocks.[9] To assess the level of competition, we rely on the number of lead underwriters or on the instrumental variable proposed by Manconi, Neretina, and Renneboog (2019). Both effects appear equally important to explain the difference in carbon premium between the primary and the secondary markets.

The main implications of our investigation for climate finance are threefold. First, firms' financial incentives to become greener via a reduction in cost of capital are lower than implied by secondary market outcomes. Second, primary market imperfections reduce the incentives for firms to reduce their carbon emissions. Our analysis suggests two improvements, a better sharing of the risk born by underwriting dealers or an increase in competition, would favor a larger carbon premium on primary markets. Third, impact/ESG/green investors should try and participate more directly in primary bond markets if they want to increase their impact on firms' financial incentives to become greener.

Our work is related to two recent papers on carbon risk in corporate bond markets. First, Seltzer et al. (2022) study whether secondary bond spreads reflect climate regulatory risk. However, they also estimate the carbon premium on the primary bond market based on carbon emissions as we do. We complement their work on the primary market by taking into account the methodological issues identified by Aswani et al. (2023a) and Zhang (2023) and by using a longer and more recent time period (2005-2022 in our case versus 2009-2017). Moreover, our empirical analysis includes a larger set of control variables: we control for coupon rate, credit rating,

[9] See also the model developed by Avramov, Lioui, Liu, and Tarelli (2022).

number of underwriting dealers, daily VIX, and fixed effects of lead underwriter identity in addition to the variables that are controlled for in Seltzer et al. (2022).

Second, Duan, Li, and Wen (2023) study how realized returns on the secondary corporate bond market depend on carbon intensity. They find that, controlling for various risk factors, portfolios including bonds issued by firms with higher carbon intensity earn lower realized returns. Their analysis suggests that this result is related to both changes in institutional ownership and to investors' underreaction to the informational content of high carbon intensity (which is correlated with future firm fundamentals). Our approach is based on expected returns and is thus closer in spirit to Bolton and Kacperczyk (2021, 2023b), Aswani et al. (2023a) and Zhang (2023). Moreover, our main contribution is the comparison of primary and secondary bond market carbon premia and the economic reasons for why they differ.

Our paper contributes to the growing literature that underscores the limited impact of sustainable finance in public markets. Using an instrumental variable methodology based on exogenous changes in Morningstar's fund ratings, Heath, Macciocchi, Michaely, and Ringgenberg (2023) finds that the impact of socially responsible funds on firms' environmental and social performance appears limited. Moreover, using inclusion and exclusion from sustainable indices, various papers find modest impact of responsible investors on stock prices, see, e.g., Hawn, Chatterji, and Mitchell (2018) and Durand, Paugam, and Stolowy (2019), for the DJSI World, and Berk and van Binsbergen (2021), for the FTSE4Good USA index. Finally, Angelis, Tankov, and Zerbib (2022) calibrate a theoretical model on US equity markets and show that the impact of green investors remains limited given the size of their assets under management and the uncertainty regarding future climate risks.

Our work is also related to three strands of literature on bond markets. First, a number of empirical papers study corporate bond market microstructure; see, e.g., Goldstein, Hotchkiss, and Nikolova (2021) on bond dealers' trading; Nikolova and Wang (2022) on flipping; Nagler and Ottonello (2021) on parking; Helwege and Wang (2021) on mega-bond issues; Hendershott, Li, Livdan, and Schürhoff (2019) on secondary market trading networks; Dick-Nielsen, Feldhütter, and Lando (2012); Bao, O'Hara, and Zhou (2018); Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018); Dick-Nielsen and Rossi (2019) on cost of liquidity provision; Cai, Helwege, and Warga (2007) on bond issuance underpricing. Our focus is different and complementary to these papers since we study the carbon premium and how it is affected by various market imperfections.

Second, there is a growing literature on green bonds; see, e.g., Zerbib (2019) on green bonds issued by a variety of supranational, sovereign, municipal and corporate institutions; Tang and Zhang (2020) on the stock price reaction to green bond issuance, Flammer (2021) on corporate green bonds, Baker, Bergstresser, Serafeim, and Wurgler (2018) on municipal green bonds, Pastor et al. (2022) on sovereign green bonds, Daubanes, Mitali, and Rochet (2022) on the reasons why firms issue green bonds. Green bonds are issued by firms, whether green or brown, with a promise, potentially certified, that the proceeds are used to finance green projects. In contrast with these studies, we study the pricing of regular bonds issued by firms with more or less carbon emissions. This enables us to consider a much larger amount of assets issued and traded in financial markets.[10]

Third, several papers focus on the link between ESG issues and bond spreads. Seltzer et al. (2022) show that corporate bond credit ratings and spreads react to issuing firms' environmental profile, especially when environmental regulations are strictly enforced. Jiraporn, Jiraporn, Boeprasert, and Chang (2014) and Amiraslani, Lins, Servaes, and Tamayo (2022) study how corporate social responsibility affects credit ratings and bond spreads during the great financial crisis, respectively. On municipal bond markets, Painter (2020) assesses the impact of physical climate risk on spreads. Garrett and Ivanov (2023) evaluates the additional bond issuance cost paid by municipalities who decide to exclude ESG-friendly underwriters.

[10]In our sample, green bonds comprise only 0.2% of the bonds. We exclude them from our main analyses but our results hold when we include them in our sample.

2 Empirical Methodology

2.1 Identification Strategy

Our main coefficient of interest is the sensitivity of bond spreads to carbon emissions, both on the primary and secondary bond market. Estimation of this coefficient can potentially be affected by three main econometric issues.

The first issue arises from calendar day effects. Bond issuance dates may be different from dates of bond trading in the secondary market. Calendar dates are thus naturally correlated with whether a particular observation belongs to the primary market or the secondary market. Moreover, price sensitivity to the CO2 emission can vary across days. Ardia et al. (2022) construct the Media Climate Change Concerns (MCCC) index and show that its unexpected time-series variations are positively correlated with changes in equity prices at the daily level (see Pastor et al. (2022) for evidence at the monthly level). Calendar date fixed effects will not address this issue because they would only deal with the impact of particular days on the level of bond spreads.

The second potential issue is related to liquidity effects. The corporate bond market is much less liquid than the equity market. Various papers document the presence of liquidity effects and liquidity risk on bond markets (Lin et al., 2011; Helwege et al., 2014; Helwege and Wang, 2021; Dick-Nielsen et al., 2012; Bao et al., 2018). Different levels of liquidity could affect bond spreads and thus the estimation of our coefficient of interest.

Lastly, credit risk also impacts bond spreads. It is challenging to empirically study this impact because credit risk is not directly observable. Credit ratings are one of the best available proxies for credit risk but their validity is less than perfect. For this reason, a number of papers (Helwege and Turner, 1999; Eom, Helwege, and Huang, 2004; Teixeira, 2007) take structural approaches. Firms could have different credit risk when they issue new bonds and when they do not. Such different credit risk, one might argue, could affect bond spreads and their sensitivity to carbon emissions.

In order to address these issues, we design an identification strategy that mimics as closely as possible the ideal strategy of comparing identical bonds that differ only in one dimension, i.e., the market in which they are traded (primary versus secondary market). In our main analysis, we consider all the dates at which firms have issued bonds. On these dates, we collect data from the bonds newly issued on the primary market and data from the bonds of the same firms issued in the past and trading on the secondary market on the issuance days.[11]

Consider for example two firms, A and B. Firm A issues its first bond, A1, on November 27th, 2020. On March 12th, 2022, it issues bond A2 and A1 was traded on the secondary market on this day. Similarly, consider that firm B issues bond B2 on January 18th, 2021. Imagine that firm B had issued bond B1 before the beginning of our sample period and that B1 was traded on the secondary market on January 18th, 2021. Using data on the issuance days, we use a cross-sectional regression to estimate the spread's sensitivity to carbon emissions both on the primary and the secondary market, controlling for firm, bond and market characteristics as well as for various fixed effects. In our example, the days included in our sample would correspond to March 12th, 2022, and January 18th, 2021.

Our approach mitigates the three potential econometric issues discussed above because we compare primary and secondary markets on the same days for the same firms, controlling for market liquidity. Our main methodology is thus a cross-sectional analysis with samples paired by firms and dates.[12] We offer various robustness tests. Moreover, in order to avoid potential liquidity spillovers from one market to the other, we also run analyses in which secondary market spreads are not measured on the issuance dates but one day before or one day after these dates.

[11]Our main analysis thus only includes in our primary market sample bonds issued by firms that have already issued bonds in the past.

[12]We cannot compute the difference, for a given firm, between the spread sensitivity to carbon emissions on the secondary and the primary market because bonds traded on the two different venues might have different characteristics in terms of maturity, amount issued, etc.

2.2 Data Construction

We use four different data sources to construct our main data. We first use S&P Global Trucost to get data on corporate carbon emissions. We rely on Mergent FISD to obtain data on corporate bond characteristics and issuance price. We get secondary market prices and trading volume data from TRACE. Lastly, we use COMPUSTAT/CRSP to get data on firm characteristics and stock returns. Our main data sample spans eighteen years, from January 2005 to March 2022. We account for inflation by converting all nominal dollar amounts into 2020 dollars.

We follow Bolton and Kacperczyk (2021) and Seltzer et al. (2022) to set up our measures of a firm's environmental profiles regarding climate change. We use a firm's Scope 1, Scope 2, and Scope 3 (upstream) carbon emissions provided by Trucost. Scope 1, also known as direct emissions, refers to carbon emitted by entities that are owned or controlled by the firm. Carbon emissions in the value chain are referred to as indirect emissions. They include Scope 2 that refers to carbon emitted by the firm's energy suppliers, and Scope 3 that refers to emissions by all other agents in the value chain. Scope 3 is itself divided into an upstream segment, that measures emissions from activities deployed to create firm's products, and a downstream segment, that measures emissions from activities that use firm's products. Similar to Bolton and Kacperczyk (2021), we leave out Scope 3 downstream due to its lack of data.

We then construct three complementary measures of carbon emissions: Scope 1 only; summing up Scope 1 and Scope 2; summing up Scope 1, Scope 2, and Scope 3 (upstream). We use them to compute a firm's carbon intensity as the ratio of carbon emissions on sales' revenue. Our main analysis favors carbon intensity over absolute carbon emissions for three reasons highlighted by Aswani et al. (2023a). First, carbon intensity is closely related to energy efficiency, an important element to reduce the social cost of the current energy transition. Second, climate regulations are likely to affect firms independently from their size. For instance, a large firm that pollutes a lot may pay a high carbon tax but, if it has large revenues, it may spread the tax over a large income. Finally, investors when tilting their portfolios towards climate-friendly firms are also unlikely to let their ranking of firms be affected by size. Nonetheless, we use the log of absolute carbon emissions in robustness analyses.

We use Mergent FISD database to obtain bond-level data on corporate bond characteristics and credit ratings (by Moody's). Bond characteristics include a flag indicating that the bond is redeemable under certain circumstances, maturity in years, and the total amount issued (logged). As typically done in the literature, we transform the letter ratings to a numerical value so that the lowest rating ("C") is assigned 1 and one notch increase gets a number larger by 1, leading the highest rating ("Aaa") to be assigned 21.

Moreover, using offering terms available from Mergent FISD database, we define offering spread as the difference between a bond's offering yield and the yield of a cash flow-matched synthetic Treasury bond. The discount rates of varying maturities derive from the U.S. Treasury yield curve provided by Gurkaynaka, Sack, and Wright (2007).

We use secondary market outcomes from TRACE to construct an illiquidity measure. We follow Amihud (2002) and Lin et al. (2011) to construct Amihud's illiquidity measure as follows:

$$ILLIQ_{i,t} = \frac{|r_{i,t}|}{Vol_{i,t}},$$

where $r_{i,t}$ is the daily return between the last day with a transaction and day t, computed on median daily prices, and $Vol_{i,t}$ is the average trading volume across these days in million dollars.[13]

We use trading data from TRACE and bond characteristics data from Mergent FISD to construct bond spreads on the secondary market. We calculate a bond's daily yield as the trading-volume weighted average of the reported yields in a given day. Then, we use a similar approach as above

[13] In studying liquidity risk in corporate bond returns, Lin et al. (2011) used two measures, introduced by Amihud (2002) and by Pastor and Stambaugh (2003), at monthly frequency. Pastor-Stambaugh measure is appropriate to construct an illiquidity measure at monthly frequency while our main analysis is at the daily level. We thus use only the Amihud measure.

to construct the yield of a cash flow-matched synthetic Treasury bond. We subtract the latter from the former to get corporate bond spreads on the secondary market. In addition, as standard in the literature (see, e.g., Liao, 2020), we exclude securities with a remaining maturity of less than a year. Lastly, for our main analysis, we focus only on the secondary market transactions that occur within two years since issuance to make the situation as comparable as possible between issuance and secondary trading.[14] Furthermore, we exclude green bonds.[15] This helps to focus on carbon emissions measured at firm level as opposed to green measures defined at the bond level. This clearly distinguishes our paper from the previous studies on green bonds. Nonetheless, in untabulated results, we show that our results are robust if we do not exclude green bonds.

Merging corporate bond and carbon emission data sets provides us with 9,022 bonds issued by 666 unique firms. Restricting the sample to bonds for which our identification strategy can be applied yields 6,036 bonds issued by 355 unique firms.

For our main analysis, we impose two additional data filters. First, as pointed out in Aswani et al. (2023a), some reported carbon emissions were estimated by the data vendor and these estimated emissions can potentially bias our empirical estimates. Thus, we follow Aswani et al. (2023a) to exclude those emissions that are estimated. More specifically, we exclude all the data with precision level 1 and 2 (See Table A11 for exact definitions of the different levels of precision). This yields 3,687 bonds issued by 229 unique firms.

The second filter relates to the seniority of the bonds. In our sample, there are 6 possible different types of seniority: senior secured, senior, senior subordinate, subordinate, junior, and junior subordinate. Given that over 96% of the bonds in our sample are senior bonds, we restrict our sample to only senior bonds. This restriction takes away 101 bonds.[16] Nonetheless, we

[14]Table A5 relaxes this filter and reproduces our main analysis.

[15]More specifically, we remove bonds whose "green bond flag" is Y by Refinitive. According to Refinitive, green bonds are fixed income products where the proceeds are used or earmarked for environmentally beneficial projects. This also includes ESG bonds where the proceeds are used only for environmental projects.

[16]The seniority filter does not take away any form in our sample because this filter is at the bond level and

show in Table A4 that our results are robust when we do not impose these two data filters.

2.3 Summary Statistics

Our main sample covers 3,586 bonds issued by 219 unique US firms. In order to limit the impact of outliers, similar to Bolton and Kacperczyk (2021), we winsorize all the variables at top and bottom 1%.[17]

Insert Table 1

The related summary statistics are shown in Table 1. The natural log of carbon emissions indicate that Scope 1, 2, and 3 emissions are of the same magnitude. After taking logs, carbon emissions are not heavily skewed since the median is close to the mean. Carbon intensity measures (Scope 1, 2, and 3) indicate that a firm, on average, emits 179.6 tons of CO2 to generate one million of 2020 dollars of sales revenue.

Bond spread is on average 0.64% on the primary market, and 0.74% on the secondary market. A bond issue is underwritten by 2.2 lead underwriters on average. Amihud-illiquidity measure is low, at 0.1 on average, but has a high standard deviation of 0.6. The average rating is between “A2” and “A3”, i.e., in the investment grade category. 67.3% of the bonds are redeemable and the average number of years remaining till maturity is 11.9 years. The amount outstanding is on average around $1,002 million. The table shows the fraction of bonds that are issued thanks to various top lead-underwriters. For instance, Morgan Stanley is lead-underwriter for 24.4% of the bonds issued in our sample.

non-senior bonds that are dropped have been issued by firms that also had issued senior bonds.

[17] Table A2 shows the impact of winsorization. Our main results hold even if we do not winsorize our variables.

3 Main empirical analysis

This section develops our main analysis using the methodology introduced in Section 2.1. As indicated above, for this main analysis, we use carbon intensity measures to proxy for a firm's environmental profile in terms of climate change.

We select a subset of the whole sample in order to implement the identification strategy described above: we focus on days in which firms that have outstanding bonds trading on the secondary market issue new bonds. We have a total of 1,073 such issuance days.

We then estimate the following model:

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}. \qquad (1)$$

$Spread_{f,i,t}$ is the spread of bond i that is issued at time t by firm f. $CO2_{f,t}$ is firm f's latest carbon intensity measure available at time t. CO2 emissions are reported on an annual basis and we use the one that is publicly available at the time of bond issuance.[18] For similar reasons, we control for firm characteristics using the latest measures available, reported on a yearly basis.

Firm controls include book leverage (COMPUSTAT item: (DLC+DLTT)/AT), pre-tax interest coverage ratio (COMPUSTAT item: XINT/OIBDP), the natural log of total assets (COMPUSTAT item: AT), profitability (COMPUSTAT item: OIBDP/(lagged AT)), the natural log of sales revenue (COMPUSTAT item: SALE), annual average of stock returns, annualized standard deviation of stock returns. Bond controls include coupon rate, daily VIX, the Amihud-illiquidity measure on the secondary market, the remaining years to maturity, the natural log of amount outstanding as of time t, a dummy variable indicating whether the bond is redeemable or not,

[18] We account for reporting lag as advised by Zhang (2023): in our main analysis we consider the same reporting lag for CO2 and for financial data. For financial data, we use the year indicated in COMPUSTAT item DATADATE to assess in what year financial data has been made available. We use the previous such year to make sure that data was available to financial market participants. In a robustness analysis, we check that our results hold if we add an additional year of lag for the CO2 variable. We merge Trucost and COMPUSTAT data on a fiscal year basis.

credit ratings issued by Moody's at the issuance, and number of all (both lead and non-lead) underwriters. In addition, we include calendar year, month of the year, day of the week, and industry (at the first-digit SIC code level) fixed effects.[19] Lastly, we account for lead underwriter fixed effects by including a dummy for each of the 10 major lead underwriters based on the dollar amount of bonds underwritten in our sample period. They include high profile investment banks such as J.P. Morgan, Citi, and Goldman Sachs.

We first estimate the model for the primary market. We then estimate the model for the secondary market price. We include the same controls in both regressions except for the illiquidity measure that is not available for the primary market. The results are summarized in Table 2.

Insert Table 2

Table 2, Columns (5) and (6) focus on the primary and secondary market, respectively. They display the results of our main regression of corporate bond spreads on carbon intensity based on the sum of Scope 1, 2 and 3 emissions. Spreads are positively sensitive to carbon intensity, both on the primary and on the secondary market. This indicates that there is a carbon premium on bond markets.

Combining these results with the summary statistics offered in Table 1 enables us to assess the economic significance of these results. On the primary market, a one standard deviation increase in carbon intensity leads to a 1.2 basis points (bps) increase in spread ($= 0.00267 \cdot 4.662 \cdot 100$). This is in line with the results reported by Seltzer et al. (2022) on a different sample period and using different environmental profile of firms. This can be compared to the average spread equal to 68 bps on the primary market. The carbon premium on the primary market thus appears low,

[19] It could be interesting to include firm-level fixed effects. However, our identification strategy significantly reduces the number of observations per firm and makes it tougher to include firm-level fixed effects. Nonetheless, in the larger secondary bond market sample that is not restricted to our specific identification strategy, we show that bond spread's sensitivity to CO2 emission is not affected by the inclusion of firm fixed effects. Moreover, Table A3 shows that our results hold even when we use one-digit SIC code interacted with year to account for industry-year fixed effects or two-digit SIC codes to account for finer industry fixed effects.

even if statistically significant. On the secondary market, a one standard deviation increase in carbon intensity leads to a 8.5 bps increase in the secondary market ($= 0.0183 \cdot 4.662 \cdot 100$). To the best of our knowledge, our paper is the first to report a significant carbon premium on the secondary corporate bond market (t-statistics are greater than 6).

Our main result is obtained by comparing the carbon intensity coefficient displayed in Table 2, Columns (5) and (6): the corporate bond spread sensitivity to carbon intensity is around 6 times larger on the secondary than on the primary market. In other words, the carbon premium is much larger on the secondary than on the primary market.

In order to test the statistical significance of this difference in sensitivity, we adopt the following approach. We first stack the primary market data and secondary market data together. We then generate an indicator variable, called $Secondary_{f,i,t}$, and we set it to 1 for a secondary market observation and 0 otherwise. Then, we interact the indicator variable with carbon intensity as well as with all the controls and fixed effects. The coefficient on the interaction term between $Secondary_{f,i,t}$ and $CO2_{f,t}$ shows the difference between the sensitivity to carbon intensity on the secondary and on the primary market.

We thus estimate the following pooled-regression model:

$$\begin{aligned} Spread_{f,i,t} = {} & \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\ & + BondControls_{f,i,t} + Secondary_{f,i,t} \times BondControls_{f,i,t} \\ & + FirmControls_{f,t} + Secondary_{f,i,t} \times FirmControls_{f,t} \\ & + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t}, \end{aligned} \tag{2}$$

where $Spread_{f,i,t}$ is spread of the bond i that is issued at time t by firm f. The results of our pooled-regression model are in Table 3, Column (3). The main coefficient of interest, β_2, is related to the interaction and is estimated to be 0.0156 with t-statistics above 5. The results are robust to clustering standard errors at the firm-level, which accounts for correlated error terms within firm.

Insert Table 3

The above estimation allows sensitivities to all the controls and fixed effects to differ between the primary and the secondary market. In order to test whether this specification affects our results, we offer the following alternative pooled-regression model:

$$
\begin{aligned}
Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} + BondControls_{f,i,t} \\
&+\beta_3 \cdot Secondary_{f,i,t} \times \text{Illiquidity}_{f,i,t} + \beta_4 \cdot Secondary_{f,i,t} \times \text{Rating}_{f,i,t} \\
&+\beta_5 \cdot Secondary_{f,i,t} \times Log(Amount)_{f,i,t} + \beta_6 \cdot Secondary_{f,i,t} \times \text{Years to maturity}_{f,i,t} \\
&+\beta_7 \cdot Secondary_{f,i,t} \times \text{Number of all underwriters}_{f,i,t} \\
&+FirmControls_{f,t} + FE + \varepsilon_{f,i,t}
\end{aligned} \tag{3}
$$

The main difference with Equation (2) is that, in Equation (3), we only interact the secondary dummy variable with five of the bond control variables, illiquidity, rating, (log) amount outstanding, years to maturity, and number of all underwriters in addition to carbon emissions. Interacting the illiquidity measure appears natural because it is available for the secondary but not for the primary market. Likewise, the rating is issued at issuance and thus reflects stale information for bonds traded on the secondary market. Interacting the amount outstanding also appears adequate because it is expected to influence differently the primary and secondary markets: a higher amount issued may increase the spread on the primary market due to liquidity pressure while a larger amount outstanding might decrease the spread on the secondary market because it makes it easier to find trading counterparts. As supporting evidence for this reasoning, the spread sensitivity to Log(Amount) is estimated to be positive in the primary market whereas it is negative in the secondary market as shown in Table 2. Since market participants who buy on the primary and those who buy on the secondary market have different holding periods, they are likely to care differently about bond duration. We thus also interact years to maturity, an approximation for duration, in our constrained pooled regression. The number of all (both lead and non-lead) underwriters might be more relevant for the secondary than for the primary market because one of their major roles is to ensure liquidity on the secondary market. As supporting evidence for this reasoning, the spread sensitivity to the number of all underwriters is non-significant on the primary market whereas it is negative on the secondary market as shown in Table 2. Besides these five bond characteristics, we do not allow other sensitivities to vary between the primary market and the secondary market.

The results of this constrained pooled regression are in Table 4. Focusing on the Scope 1, 2 and 3 carbon intensity measure, the main coefficient of interest, β_2, is still positive and statistically significant: it is estimated to be 0.00568 with a t-statistics of 2.192. Our results thus hold even if we restrict most of the explanatory variables to have the same effect on primary and secondary bond markets. Such a constraint appears rather strong from an economic point of view so we use the unconstrained pooled regression as our main empirical model.

Insert Table 4

Taken together, our results indicate that bond spreads on the secondary market are significantly more sensitive to issuing firms' carbon intensity than those on the primary market. This is the main contribution of our paper. Firms' financial incentives to become greener are related to primary market outcomes that directly affect the cost of capital. Our main result has important implications for the strength of these incentives. Indeed, our main result suggests that the direct incentives financial markets provide firms for becoming greener appear to be lower than one could think by looking at secondary markets. This is particularly relevant given that studies measuring the carbon premium (on the equity market) focus on the secondary market (see, e.g., Bolton and Kacperczyk, 2021, 2023b; Chava, 2014; Pastor et al., 2022).

For completeness, we also display the results for other emission measures separately. Table 2, Columns (1) and (2) use Scope 1 intensity measure and Columns (3) and (4) use Scope 1+2 intensity measure. Table 3, Columns (1) and (2) show our estimate of β_2 in Model 2 for Scope 1 and Scope 1 and 2, respectively. The similar estimates under the constrained model (Equation (3)) are summarized in Table 4, Columns (1) and (2). As shown, our main result applies to different scopes of carbon emissions: bond spreads are significantly more sensitive to carbon intensity on the secondary than on the primary market.[20]

4 Additional empirical analyses

This section offers additional analyses that refine our main insights and that test the robustness of our main results. All the tests of difference between the primary and the secondary market carbon premium are based on the pooled regression model indicated in Equation (2).

4.1 Time-series analysis

We start by studying whether we can detect in the time-series our main result that sensitivity to carbon intensity is higher on the secondary than on the primary market. As already indicated, our main analysis favors a cross-sectional approach because it better deals with the potential influence of calendar day effects: the carbon premium could differ across markets due to differences in dates of trading and in the associated supply and demand characteristics. However, we thought it could be useful to check whether our main result is also found in the time-series so that we can offer a graphical illustration of our main insights.

In our time-series analysis, we use the number of months since offering to construct a rolling window. The first rolling window is the offering day and it is denoted as month 0. The second rolling window, named month 1, is between one day and one month since the bond offering;

[20] It is worth discussing how our results relate to the literature that documents underpricing in the corporate bond issuance. Cai et al. (2007) show that offering spreads (on the primary market) are larger than the trading spread (on secondary market), in a similar spirit to the equity IPO underpricing. Our main results show that spread sensitivity to carbon intensity is lower on the primary than on the secondary market. Our results might appear as contradicting the underpricing result. However, we focus on the spread's sensitivity to carbon intensity, whereas the underpricing literature focuses on the level of the spread. We are thus not studying the same phenomenon.

the third rolling window, named month 2, is between one month and two months since the bond offering, etc.

We restrict our sample to bonds of firms that have not yet updated their emission report. Given that CO2 emissions are annually reported, this restriction mechanically means that months since offering in our restricted sample cannot be greater than 12 months. Realistically, we have sufficient number of observations, i.e., trading prices, when months since offering are equal to or less than 10 months. We thus have the following sample: 3,237 primary market prices for month 0, 40,980 for month 1, 42,259 secondary market prices for month 2, 35,783 for month 3, 33,206 for month 4, 29,681 for month 5, 24,673 for month 6, 22,277 for month 7, 19,462 for month 8, 13,855 for month 9, and 9,765 for month 10. Table A10 shows the related summary statistics.

For each rolling window, we estimate the model displayed in Equation (1), with t referring to rolling-window months. We plot β over different rolling windows in Figure 1 using carbon intensity measured as the sum of Scope 1, 2 and 3 emissions.

Insert Figure 1

The figure is in line with our main results. The spread is positively sensitive to CO2 emission intensity both on the primary market (depicted as month 0 in the figure) and on the secondary market. This result is statistically significant at 95% confidence level. Moreover, the secondary market spread sensitivity is statistically different from the primary market sensitivity, starting five months after the offering. This illustrates our main findings. In order to show that the pattern is not specific to a particular definition of CO2 emissions, we plot the results for Scope 1 and Scope 1 and 2 carbon intensities in Figures A2 and A3, respectively, in the Appendix.

4.2 Shocks to climate change concerns

In this section, we study how the carbon premium arising in bond spreads reacts to changes in climate change concerns. For this cross-sectional analysis, we closely follow the methodology applied by Pastor et al. (2022) and Ardia et al. (2022) to equity prices. More specifically, we measure shocks to climate change concerns as prediction errors from AR(1) models with controls (denoted as CTRL-6 in Ardia et al.) applied to the monthly Media Climate Change Concerns (MCCC) index constructed by Ardia et al. (2022). We measure the shocks based on the past 36 months of data. Then, we estimate how much the carbon premium is sensitive to the shock to climate change concerns by estimating the following model:

$$\begin{aligned} Spread_{f,i,t} = & \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot CS_t + \beta_3 \cdot CS_t \times CO2_{f,t} \\ & + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}, \end{aligned} \tag{4}$$

where CS_t is the last available monthly climate shock at time t. The main variable of interest is the interaction term, $CS_t \times CO2_{f,t}$, and the associated coefficient, β_3. We document the results in Table 5.

This analysis yields two findings. First, the corporate bond carbon premium is positively sensitive to climate concerns shocks, similar in spirit to what is empirically observed in the corporate equity market. Second, our main results hold when we add shocks to climate change concerns in our regressions.

Insert Table 5

4.3 Investment-grade

In order to test whether our main results vary across firms' credit worthiness, we do a subsample analysis based on bonds' credit ratings at issuance. We estimate Equation (1) for investment-grade and report the results in Table 6. It shows that our main result holds when we focus on investment grade bonds. Effects for high yield bonds cannot be estimated due to insufficient data.

Insert Table 6

4.4 Brown industry indicator

This subsection studies whether our main result is robust to different proxy for firms' greenness. In particular, compared to our benchmark case, we use brown industry indicator as main regressor. The indicator is set 1 if two-digit SIC code's CO2 emission is above the median. Otherwise, it is sets to 0. We document the related results in Table 7.[21]

Insert Table 7

As shown, the sensitivities to brown industry indicator are positive and statistically significant in both primary market and secondary market. Most importantly, the differential sensitivity between the two markets is positive and statistically significant (e.g. their t-stat is 13.39 when we use Scope 1,2, and 3 emission measure). This shows that our results are robust to different proxy for firms' greenness.

4.5 Absolute CO2 emissions

Our main analysis focuses on carbon intensity as a measure of CO2 emissions by firms, as advocated by Aswani et al. (2023a). This subsection however studies whether our results hold when we use absolute CO2 emissions. This is also a relevant emission metrics since, as reminded

[21] This analysis is feasible because our industry fixed effects consider 1-digit SIC codes.

by Bolton and Kacperczyk (2023b), what matters for climate change is the absolute amount of CO2 emitted in the atmosphere. We thus repeat our main analysis and estimate Equation 1 by replacing carbon intensity by the log of absolute emissions. The results are in Table 9.

Insert Table 9

The two main insights from Table 9 are consistent with our main results. First, we find that spreads on both the primary and the secondary market are sensitive to absolute emissions. Second, the secondary market sensitivity appears larger than the primary market one as the difference is statistically significant for all three different measures. One standard deviation increase in absolute CO2 emission leads to a 1.9 basis points increase in the primary market spread $(= 0.0157 \cdot 1.229 \cdot 100)$ and a 14.4 basis points increase in the secondary market $(= 0.117 \cdot 1.229 \cdot 100)$. We conclude from this additional analysis that financial market participants focus on both carbon intensity and absolute carbon emissions when incorporating climate change issues in bond pricing.

4.6 Robustness analysis

4.6.1 Liquidity Risk

Corporate bonds pricing is sensitive to illiquidity risk (Lin et al., 2011; Dick-Nielsen et al., 2012; Bao et al., 2018). Accordingly, our main cross-sectional specification includes Amihud (2002)'s illiquidity measure as well as the total amount issued as control variables. However, one concern related to the illiquidity measure could be that bonds of a given firm trading on the secondary market might have different illiquidity on the days in which the firm issues a new bond and on the other days. In other words, an issuance on the primary market could affect liquidity on the secondary market. This could induce a bias in the carbon premium that we measure on the secondary market. We here focus on the secondary market only and provide two pieces of evidence to alleviate this concerns.

We first show that Amihud (2002)'s illiquidity measure is similar across days with a new bond issuance and days just before or after the issuance. When a given firm issues new bonds, its outstanding bonds' Amihud-illiquidity measure is 0.112 with standard deviation of 0.776. On the days before and after the same firm issues new bonds, the outstanding bonds' Amihud-illiquidity measure is 0.106 with standard deviation of 0.751. The difference between these numbers is statistically insignificant with a t-test of 1.04.

We then show that bond spreads' sensitivity to CO2 intensity on the secondary market does not depend on the days we use to measure spreads, whether it is on the day of the issuance or on the days just before and after the issuance. In order to show this, we estimate Equation 1 for days just before and just after a given firm issues a new bond. Table 10, Columns (2), (4) and (6) include our estimation results. For ease of comparison, Table 10, Columns (1), (3), and (5) reproduce the estimates obtained when secondary market spreads are measured on the day of the issuance, as they appear in Table 2. The price sensitivity to CO2 emissions are not statistically different between the two specifications. The t-statistics is 0.10 between Columns (1) and (2), 0.37 between (3) and (4), and 0.41 between (5) and (6).[22]

Insert Table 10

4.6.2 More precise measurement of CO2 emissions

As discussed in Section 2, we rule out CO2 measures that are indicated by S&P Global Trucost as estimated. However, the other carbon emissions offered by the data provider may also include some kind of estimation with varying precision. In this subsection, we show that our main results are robust to these different degrees of estimation precision.

We first define different degrees of estimation precision as follows. In some cases, firms disclose their CO2 emission via their 10-K report or via CDP (carbon disclosure project) and the reported

[22]Unreported tables show that our main results also hold when we estimate Equation 1 on the days just before and just after issuance, separately, and when we estimate Equation 1 on the days of issuance but without including Amihud-illiquidity measure as a control or by replacing it by trading volume.

number is gathered and made available to the researchers by Trucost. In other cases, due to the lack of reported numbers, the data vendor estimates the firms' CO2 emission based on many different sources such as the firms' production data. As such, there are different degrees of precision levels to the reported CO2 emissions. Trucost documents how the reported CO2 emissions were derived and there are 32 different types in total. We assign each type to different precision level and report our classification in Table A11. For instance, "Exact value from CDP" is assigned to the most precise level, 5. "Estimate derived from production data" is assigned to the most imprecise level, 1. Our classification is more granular but consistent with the one used by Aswani et al. (2023a): our level-5 precision corresponds to their type (ii) emissions: directly disclosed total emissions.

Next, we use our classification to construct different sub-samples. The precision level for a given firm's Scope 1 measure might not be the same as the one for the same firm's Scope 2 measure. Nonetheless, when we use Scope 1 measure, we restrict the sample based on both Scope 1 and Scope 2 precision level. This helps us to do apple-to-apple comparison across different results obtained using different CO2 emission measures. We do not apply the filters based on the precision level for the Scope 3 due to data unavailability.

We construct a first sub-sample by restricting the sample to observations with CO2 emissions' reporting precision level of 4 or above. We run our main specification, displayed in Equation (1). The cross-sectional estimation results are in Table 11, Panel A.

Insert Table 11

Our main results stay robust. For instance, when we use the sum of Scope 1, 2 and 3 measure, the difference in the sensitivities between the two markets is positive and statistically significant with t-statistics of 5.696. The magnitude of this difference is similar to our main results, summarized in Table 2. This suggests that, in our analysis, the precision issue highlighted by Aswani et al. (2023a) is not driving our main results.

Similarly, we construct a second sub-sample by restricting the sample to observations with CO2 emissions' reporting precision level equal to 5. The estimates appear very similar both in levels and in statistical significance. This shows the robustness of our results and indicates that getting rid of the lower CO2 emissions' reporting precision, level 1 and 2, as we do in our main analyses is enough to get an accurate picture of our results.

4.6.3 Different subsamples based on time

This subsection studies whether our main result is robust to different subsamples based on time. We first split our sample in two and run our main cross-sectional analysis on a sub-sample ranging from 2005 to 2013, and on another one ranging from 2014 to 2022. We document the related results in Table 8, Panel A1 and A2. In both time periods, the carbon premium is positive and statistically significant for the secondary market, both in the old and recent time periods. On the primary market, the carbon premium is positive but only significant during the old time period. Our main result that the carbon premium is larger on the secondary than on the primary market holds for the two time periods.

Insert Table 8

Next, we divide our sample into two subsets, odd years and even years. We document the related results in Table 8, Panel B1 and B2. In both subsamples, the carbon premium is positive and statistically significant for the secondary market, both in the odd and even years. On the primary market, the carbon premium is positive but only significant during the odd years period. Our main result that the carbon premium is larger on the secondary than on the primary market holds for the two subsamples.

These robustness analyses suggest that the carbon premium on the primary market is much less statistically robust than the carbon premium on the secondary market. On the other hand, our main result that the carbon premium is significantly larger on the secondary than on the primary market is robust over the different subsamples.

5 Potential economic channels

Our previous empirical analyses document that corporate bond spreads are less sensitive to carbon intensity on the primary than on the secondary market. In other words, the carbon premium is lower on the primary than on the secondary market. In this section, we study two potential economic channels that could rationalize this observation: an uncertainty channel, related to the future climate concerns of investors, and a competition channel.

5.1 A conceptual analysis

The appendix offers a very stylized model that can rationalize our main result and that points towards our two channels of interest. The model features a primary market with two types of participants without green preferences: underwriting dealers who liquidate their position on the secondary market and investors who hold their position up to maturity.[23] On the secondary market, investors with climate concerns trade with dealers. Despite the absence of green preferences among primary market participants, the issuance price reflect expected green concerns as they matter for the price at which dealers are liquidating their position. However, climate concerns are not fully reflected in the issuance price because some investors without green preferences are also trading on the primary market. The primary price is thus less sensitive to expected climate concerns, for example measured by carbon intensity as in our empirical analyses. This rationalizes our main findings.

When there is more uncertainty regarding the strength of climate concerns on the secondary market, dealers are less aggressive on the primary market due to their risk aversion. This implies that the views of investors with no green preferences weigh larger in the issuance price. This leads to our first channel according to which, when there is more uncertainty on climate concerns, the difference in sensitivity to carbon emissions between the secondary and the pri-

[23] A more general model in which primary market investors have green preferences could also rationalize our empirical findings for some parameter values. For brevity, we restrict our attention to the simple case in which investors on the primary market do not care about climate change.

mary market spreads is larger.

When there is less competition between underwriting dealers on the primary market, they reduce their aggressiveness to increase their trading profits. As a result, their views, linked to secondary market investors' climate concerns, are less reflected into the issuance price, and the views of investors with no green preferences weigh larger. This leads to our second channel according to which, when there is less competition, the difference in sensitivity to carbon emissions between the secondary and the primary market spreads is larger. These two channels are tested in the next subsections based on triple interaction analyses.

5.2 Uncertainty Channel

Our theoretical analysis yields the following testable prediction: the difference between the sensitivity to carbon intensity on the secondary and the primary market increases as future climate change concerns become more uncertain.

In order to test this prediction, we first construct a dummy variable HV_t that indicates a high uncertainty at time t regarding future climate concerns. For this, we use daily Media Climate Change Concerns index that was constructed and was made available to download by Ardia et al. (2022). To estimate the conditional volatility at day t, we use an ARCH model with 30 lags, from $t-30$ and $t-1$. It is worth mentioning that this uncertainty is different from the shock to the climate concerns that we used in Section 4.2 and were constructed at the monthly level. Then, we set $HV_t = 1$ if the conditional volatility is above the median. Otherwise, we set it to 0. Then, we estimate the following model:

$$
\begin{aligned}
Spread_{f,i,t} = & \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot HV_t + \beta_3 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\
& + \beta_4 \cdot CO2_{f,t} \times HV_t + \beta_5 \cdot Secondary_{f,i,t} \times HV_t + \beta_6 \cdot Secondary_{f,i,t} \times CO2_{f,t} \times HV_t \\
& + BondCtrl_{f,i,t} + Secondary_{f,i,t} \times BondCtrl_{f,i,t} + FirmCtrl_{f,t} \\
& + Secondary_{f,i,t} \times FirmCtrl_{f,t} + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t}
\end{aligned} \tag{5}
$$

where $Spread_{f,i,t}$ is spread of the bond i that is issued on day t by firm f. Our main variable of interest is the triple interaction term, $Secondary_{f,i,t} \times CO2_{f,t} \times HV_t$. Testing the prediction is equivalent to testing whether β_6 is positive or not. Table 12 summarizes the relevant results. The coefficient β_6 is estimated to be statistically significant and positive when one uses any of the three scope measures of carbon intensity.

Insert Table 12

5.3 Competition among underwriters

Our theoretical analysis yields the following testable prediction: the difference between the sensitivity to carbon intensity on the secondary and the primary market increases as the level of competition between underwriting dealers diminishes.

In order to test this second prediction, we first construct a dummy variable, $LC_{f,i}$, that indicates a low level of competition among underwriters for bond i issued by firm f. Because lead underwriters determine the issuance price, we use the number of lead underwriters to measure competition. Moreover, bonds with larger offered amount mechanically have larger number of lead underwriters. In order to address this, we scale the number of lead underwriters by the amount issued and compute:

$$
Ratio = \frac{\text{Number of lead underwriters}}{\text{Amount offered}}.
$$

We set $LC_{f,i} = 1$ if *Ratio* is below the median. Otherwise, we set it to 0.[24][25] We then estimate the following model with a triple interaction term:

$$\begin{aligned} Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot LC_t + \beta_3 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\ &+ \beta_4 \cdot CO2_{f,t} \times LC_t + \beta_5 \cdot Secondary_{f,i,t} \times LC_t + \beta_6 \cdot Secondary_{f,i,t} \times CO2_{f,t} \times LC_t \\ &+ BondCtrl_{f,i,t} + Secondary_{f,i,t} \times BondCtrl_{f,i,t} + FirmCtrl_{f,t} \\ &+ Secondary_{f,i,t} \times FirmCtrl_{f,t} + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned} \tag{6}$$

$Spread_{f,i,t}$ is the spread of bond i is issued on day t by firm f. Our main variable of interest is the triple interaction term, $Secondary_{f,i,t} \times CO2_{f,t} \times LC_{f,i}$. Testing our prediction is equivalent to testing whether β_6 is positive or not. Table 13 summarizes the relevant results. The coefficient β_6 is estimated to be statistically significantly positive for all three measures of CO2 emissions.

Insert Table 13

The economic impact of the two channels we document are of similar magnitude. Because the triple interaction variables have the same standard deviation, we can directly compare the estimated coefficients, β_6. These coefficients are 0.0204 and 0.0232 for the uncertainty and the competition channel, respectively, on Scope 1, 2 and 3 emission intensity. They are not significantly different from each others (t-statistics is 0.31). We conclude that the uncertainty and competition channels are equally important to explain why the carbon premium is not as large on the primary than on the secondary market.[26]

[24] The correlation between the two dummy variables, HV_t and $LC_{f,i}$, appears low and equal to 0.055.

[25] For robustness, we use a different proxy to construct $LC_{f,i}$. We first compute the ease with which a firm can find a lead underwriter given the type of bond it issues, as proposed by Manconi et al. (2019). Then, we set $LC_{f,i} = 1$ if the ease to find a lead underwriter is below the median. Otherwise, we set it to 0. The results reported in the appendix are qualitatively similar.

[26] We reach similar conclusion when both channels are included as summarized in Table A9.

6 Conclusion

Do green firms with low carbon emissions benefit from a lower cost of capital than brown firms? Or instead, do financial intermediaries on the primary market reap part of the carbon premium in the form of higher returns on their intermediation activities at issuance? We address these issues by comparing the carbon premium on primary and secondary bond markets. Using a sample of 219 US firms active in the bond market from 2005 to 2022, we establish our main result: there is a carbon premium that appears larger on the secondary than on the primary market. Our main specification features a cross-sectional analysis which compares, for a given firm at a given bond issuance date, the carbon premium on the primary market and on the secondary market for bond(s) of the same firm that were issued before. Our main result also holds in the time series, comparing bonds' carbon premium evolution over time from issuance on the primary market to trading on the secondary market, as well as for a variety of robustness checks.

Our evidence suggests that two economic forces underlie our main result. The part of the carbon premium pocketed in by financial intermediaries appears related i) to uncertainty regarding investors' future climate concerns and ii) to a lack of competition among underwriting dealers. These two effects appear equally important in driving our main result.

The main implications of our investigation are threefold. First, the impact of investors with green preferences on firms' financial incentives to become green is lower than implied by secondary market outcomes. Second, market microstructure frictions are detrimental to these incentives. Third, green investors should try and participate more directly in primary bond markets if they want to increase their impact on firms' financial incentives to become green.

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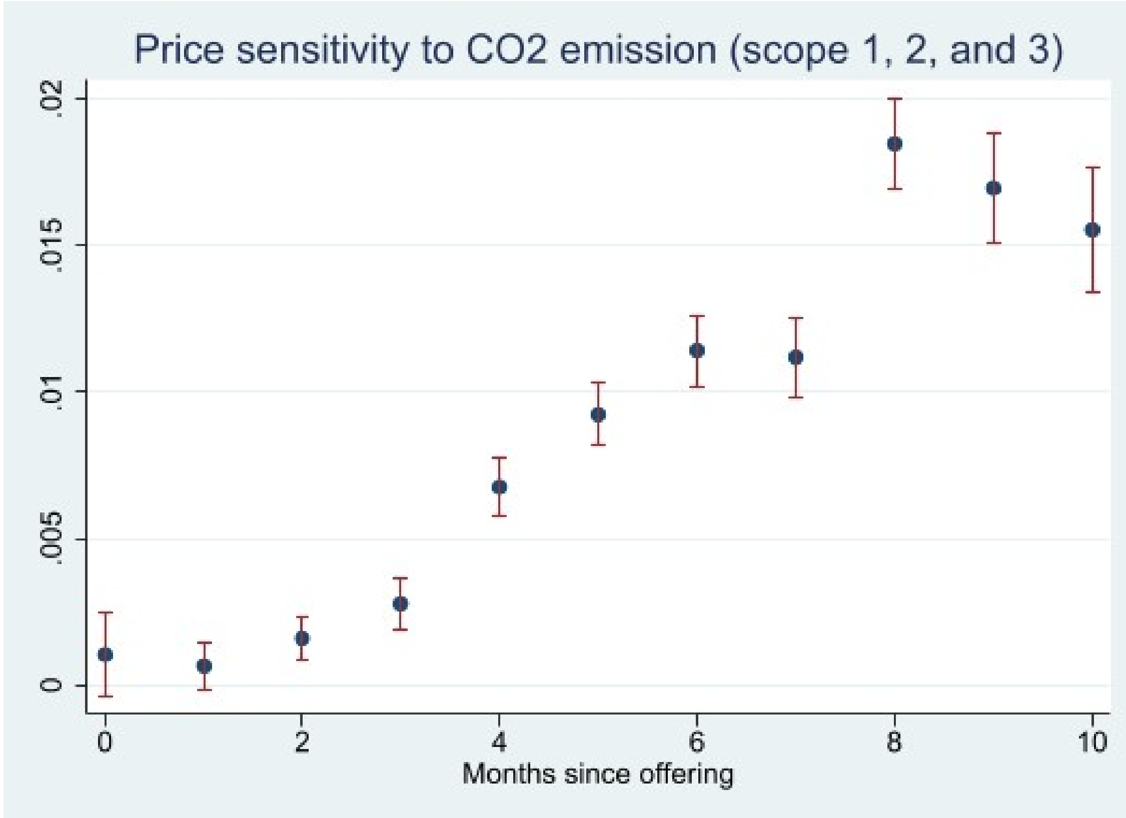


This figure illustrates how price sensitivities to CO2 emission change over months since offering. We use the number of months since offering to construct rolling window. The first rolling window is the offering day and it is denoted as 0 months. The second rolling window is between 1 day and 1 month since the bond offering. The third rolling window is between 1 month and 2 months since the bond offering... For each rolling window, we run the following panel regression:

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}.$$

$Spread_{f,i,t}$ is the spread of bond i that is issued at time t by firm f. $CO2_{f,t}$ is firm f's latest carbon intensity measure available at time t. Then, we plot β over different rolling windows when we use CO2 intensity measure for Scope 1, 2, and 3.

Figure 1: Price sensitivities to Scope 1, 2, and 3 carbon emissions in the time-series

Table 1: Summary Statistics

Our data sample covers 3,586 bond issues from 219 unique US firms. The sample spans from 2005 to 2022. We winsorize all the variables at top and bottom 1%. The first panel summarizes CO2 emission measures. We use firms' Scope 1, Scope 2, and Scope 3 (upstream) carbon emissions. Scope 1 and Scope 2 are correlated at 0.263, Scope 1 and Scope 3 are correlated at 0.297 and Scope 2 and Scope 3 are correlated at 0.277. We normalize them by firms' sales to get carbon intensity measures. The second panel shows firm characteristics. The third panel summarizes bond characteristics. We define offering/secondary spread as the difference between a bond's yield and the yield of a cash flow-matched synthetic Treasury bond. We transform the letter ratings to a numerical value so that one notch increase gets a number larger by 1 (e.g. "C" is assigned 1 and "Aaa" is assigned 21). We use Amihud's illiquidity measure.

	N	Mean	SD	Median
CO2 emission measures				
Log(Carbon Emission Scope 1 (tons CO2e))	219	11.67	2.104	11.50
Log(Carbon Emission Scope 1 and 2 (tons CO2e))	219	13.81	1.514	13.84
Log(Carbon Emission Scope 1, 2, and 3 (tons CO2e))	219	15.16	1.229	15.17
Carbon intensity Scope 1 (tons CO2e/USD m.)/100	219	0.746	3.912	0.0104
Carbon intensity Scope 1 and 2 (tons CO2e/USD m.)/100	219	0.979	4.092	0.133
Carbon intensity Scope 1, 2, and 3 (tons CO2e/USD m.)/100	219	1.796	4.662	0.429
Firm characteristics				
Book leverage	219	0.354	0.160	0.364
Interest coverage ratio	219	0.189	0.216	0.118
Firm size	219	12.67	1.521	13.21
ROA	219	0.0942	0.0920	0.0343
Firm sale	219	10.89	0.873	10.83
Equity return mean	219	0.109	0.278	0.125
Log(Equity return vol)	219	-1.523	0.415	-1.594
Bond characteristics				
Offering spread (%)	2536	0.641	0.599	0.471
Secondary spread (%)	2579	0.741	1.046	0.702
Number of lead underwriters	3586	2.163	1.293	2
Number of all underwriters	3586	4.495	1.708	5
Illiquidity	3586	0.0970	0.592	0.000567
Rating (Moody's)	3586	15.24	2.225	15
$\mathbb{1}\{\text{Redeemable}\}$	3586	0.673	0.469	1
Years to maturity	3586	11.85	9.886	8.764
Amount outstanding (millions)	3586	1,002	954.1	768.9
Coupon (%)	3586	3.843	1.454	3.850
$\mathbb{1}\{\text{Lead underwritten by J.P. Morgan}\}$	3586	0.211	0.408	0
$\mathbb{1}\{\text{Lead underwritten by Citi}\}$	3586	0.184	0.387	0
$\mathbb{1}\{\text{Lead underwritten by Merrill Lynch}\}$	3586	0.215	0.411	0
$\mathbb{1}\{\text{Lead underwritten by Barclays}\}$	3586	0.112	0.315	0
$\mathbb{1}\{\text{Lead underwritten by Morgan Stanley}\}$	3586	0.244	0.430	0
$\mathbb{1}\{\text{Lead underwritten by Goldman Sachs}\}$	3586	0.164	0.371	0
$\mathbb{1}\{\text{Lead underwritten by Wells Fargo}\}$	3586	0.0735	0.261	0
$\mathbb{1}\{\text{Lead underwritten by Deutsche bank}\}$	3586	0.0833	0.276	0
$\mathbb{1}\{\text{Lead underwritten by Bank of America}\}$	3586	0.0406	0.197	0

Table 2: Main Result
(1), (3), and (5) report the results when the model is estimated on the primary market whereas (2), (4), and (6) report the results estimated on the secondary market.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.00251**	0.0158***	0.00273***	0.0180***	0.00267***	0.0183***
	(2.418)	(6.514)	(2.723)	(7.632)	(2.901)	(8.543)
Years to maturity	0.0154***	0.0543***	0.0154***	0.0544***	0.0154***	0.0545***
	(22.71)	(49.59)	(22.76)	(49.72)	(22.78)	(49.84)
Log(Amount)	0.0305***	-0.0243***	0.0304***	-0.0245***	0.0304***	-0.0246***
	(7.176)	(-4.715)	(7.169)	(-4.742)	(7.162)	(-4.769)
$\mathbb{1}\{\text{Redeemable}\}$	0.0588***	0.173***	0.0588***	0.174***	0.0589***	0.175***
	(2.986)	(7.742)	(2.990)	(7.777)	(2.992)	(7.829)
Rating (Moody's)	-0.0156***	-0.0611***	-0.0156***	-0.0609***	-0.0156***	-0.0603***
	(-5.656)	(-11.50)	(-5.656)	(-11.46)	(-5.657)	(-11.37)
Number of all underwriters	-0.00564	-0.0160**	-0.00563	-0.0160**	-0.00564	-0.0159**
	(-1.210)	(-2.466)	(-1.209)	(-2.463)	(-1.210)	(-2.447)
Illiquidity		0.0242**		0.0243**		0.0244**
		(2.284)		(2.297)		(2.306)
Coupon	0.342***	-0.00491	0.342***	-0.00553	0.342***	-0.00582
	(51.35)	(-0.534)	(51.33)	(-0.602)	(51.28)	(-0.635)
VIX (daily)	0.00688***	0.0325***	0.00689***	0.0325***	0.00689***	0.0325***
	(7.350)	(21.41)	(7.370)	(21.41)	(7.372)	(21.45)
Equity return mean	-0.0943***	-0.466***	-0.0940***	-0.462***	-0.0934***	-0.460***
	(-3.105)	(-9.136)	(-3.096)	(-9.081)	(-3.078)	(-9.040)
Log(Equity return vol)	0.0699***	0.282***	0.0703***	0.283***	0.0708***	0.287***
	(3.829)	(8.997)	(3.850)	(9.059)	(3.877)	(9.175)
Book leverage	0.0749	0.303***	0.0747	0.303***	0.0706	0.288***
	(1.479)	(3.890)	(1.477)	(3.904)	(1.398)	(3.708)
ROA	-0.0335	-0.763***	-0.0267	-0.717***	-0.0189	-0.666***
	(-0.332)	(-3.768)	(-0.264)	(-3.541)	(-0.186)	(-3.284)
Interest coverage ratio	-0.205***	-0.662***	-0.206***	-0.661***	-0.205***	-0.656***
	(-4.040)	(-10.80)	(-4.062)	(-10.80)	(-4.043)	(-10.74)
Firm sale	0.0150	0.0200	0.0154	0.0235	0.0149	0.0219
	(1.473)	(1.001)	(1.515)	(1.179)	(1.467)	(1.105)
Firm size	-0.00204	-0.000757	-0.00179	0.000530	-0.000956	0.00553
	(-0.209)	(-0.0398)	(-0.184)	(0.0278)	(-0.0978)	(0.291)
Observations	2,428	8,525	2,428	8,525	2,428	8,525
R-squared	0.839	0.630	0.839	0.631	0.839	0.631
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Main Result: Pooled Regression

The table reports our main results by comparing the carbon intensity coefficient displayed in Table 2 between secondary and primary market. In order to test the statistical significance of this difference in sensitivity, we first stack the primary market data and secondary market data together. We then generate an indicator variable, called $Secondary_{f,i,t}$, and we set it to 1 for a secondary market observation and 0 otherwise. Then, we interact the indicator variable with carbon intensity as well as with all the controls and fixed effects. The coefficient on the interaction term between $Secondary_{f,i,t}$ and $CO2_{f,t}$ shows the difference between bond spread's sensitivity to carbon intensity on the secondary and on the primary market. We thus estimate the following pooled-regression model:

$$\begin{aligned} Spread_{f,i,t} = & \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} + BondControls_{f,i,t} \\ & + Secondary_{f,i,t} \times BondControls_{f,i,t} + FirmControls_{f,t} + Secondary_{f,i,t} \times FirmControls_{f,t} \\ & + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned}$$

The table reports the estimates of β_2. Column (1) reports the results when Scope 1 and 2 intensity measure is used. Column (2) reports the results when Scope 1 is used. Column (3) reports the results when Scope 2 is used.

	(1) Scope 1 Primary + Secondary	(2) Scope 1 and 2 Primary + Secondary	(3) Scope 1, 2, and 3 Primary + Secondary
CO2	0.00251	0.00273	0.00267
	(1.024)	(1.153)	(1.230)
CO2 X Secondary	0.0133***	0.0153***	0.0156***
	(4.053)	(4.793)	(5.380)
Observations	10,953	10,953	10,953
R-squared	0.649	0.649	0.650
Bond controls	YES	YES	YES
Firm controls	YES	YES	YES
Bond controls X Secondary	YES	YES	YES
Firm controls X Secondary	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Month FE	YES	YES	YES
DOW FE	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES
Industry X Secondary FE	YES	YES	YES
Year X Secondary FE	YES	YES	YES
Month X Secondary FE	YES	YES	YES
DOW X Secondary FE	YES	YES	YES
LeadUnderwriter1-10 X Secondary FE	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Main Result: Pooled Regression With Restrictions
The table compares the carbon intensity coefficient displayed in Table 2 between secondary and primary market.

	(1) Scope 1 Primary + Secondary	(2) Scope 1 and 2 Primary + Secondary	(3) Scope 1, 2, and 3 Primary + Secondary
CO2	0.00850***	0.00898***	0.00974***
	(3.688)	(4.042)	(4.803)
CO2 X Secondary	0.00562*	0.00702**	0.00568**
	(1.874)	(2.440)	(2.192)
Years to maturity	0.0360***	0.0361***	0.0362***
	(27.76)	(27.85)	(27.91)
Log(Amount)	0.0335***	0.0340***	0.0339***
	(4.452)	(4.516)	(4.491)
$\mathbb{1}${Redeemable}	0.171***	0.171***	0.172***
	(8.989)	(9.016)	(9.057)
Rating (Moody's)	-0.0737***	-0.0740***	-0.0736***
	(-14.65)	(-14.70)	(-14.61)
Number of all underwriters	-0.00705	-0.00668	-0.00621
	(-0.745)	(-0.706)	(-0.656)
Coupon	0.0416***	0.0411***	0.0408***
	(5.668)	(5.604)	(5.567)
VIX (daily)	0.0285***	0.0285***	0.0285***
	(23.90)	(23.91)	(23.94)
Equity return mean	-0.393***	-0.391***	-0.389***
	(-9.915)	(-9.866)	(-9.811)
Log(Equity return vol)	0.251***	0.252***	0.255***
	(10.29)	(10.35)	(10.47)
Book leverage	0.291***	0.291***	0.278***
	(4.669)	(4.685)	(4.471)
ROA	-0.805***	-0.773***	-0.736***
	(-5.386)	(-5.168)	(-4.908)
Interest coverage ratio	-0.610***	-0.610***	-0.605***
	(-11.85)	(-11.86)	(-11.78)
Firm sale	0.0228	0.0251*	0.0236
	(1.526)	(1.683)	(1.587)
Firm size	-0.00783	-0.00678	-0.00308
	(-0.551)	(-0.477)	(-0.217)
Illiquidity X Secondary	0.0334***	0.0334***	0.0336***
	(3.352)	(3.362)	(3.380)
Rating (Moody's) X Secondary	0.0374***	0.0381***	0.0379***
	(7.734)	(7.849)	(7.806)
Log(Amount) X Secondary	-0.0543***	-0.0549***	-0.0547***
	(-7.073)	(-7.155)	(-7.125)
(Years to maturity) X Secondary	0.0152***	0.0152***	0.0152***
	(11.12)	(11.11)	(11.13)
(Number of all underwriters) X Secondary	-0.0145	-0.0149	-0.0154
	(-1.407)	(-1.450)	(-1.493)
Observations	10,953	10,953	10,953
R-squared	0.613	0.614	0.614
FE	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Interaction with MCCC shocks

Table studies how the carbon premium arising in bond spreads reacts to changes in climate change concerns between year 2005 and 2018. We measure shocks to climate change concerns as prediction errors from AR(1) models with controls (denoted as CTRL-6 in Ardia et al) applied to the monthly Media Climate Change Concerns (MCCC) index constructed by Ardia et al. (2022). We measure the shocks based on the past 36 months of data. Then, we estimate how much the carbon premium is sensitive to the shock to climate change concerns by estimating the following model:

$$\begin{aligned} Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot CS_t + \beta_3 \cdot CS_t \times CO2_{f,t} \\ &+ BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}, \end{aligned}$$

where CS_t is the last available monthly climate shock at time t. The table reports the estimates of β_1 and β_3. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.0172*** (4.175) , 0.0196*** (4.957), and 0.0196*** (5.409) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.00434***	0.0213***	0.00442***	0.0238***	0.00419***	0.0236***
	(3.312)	(7.129)	(3.507)	(8.276)	(3.623)	(8.959)
CO2 X CS	0.0194***	0.0317***	0.0204***	0.0323***	0.0191***	0.0258***
	(4.922)	(3.408)	(5.345)	(3.613)	(5.551)	(3.326)
Observations	1,709	6,739	1,709	6,739	1,709	6,739
R-squared	0.844	0.645	0.845	0.646	0.845	0.647
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Investment grade

The table shows how our main result depend on the creditworthiness of the bonds. Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when Scope 1 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when Scope 1 and 2 (Scope 1,2, and 3) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

The table reports the estimates for investment grade bonds. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.0116*** (3.095), 0.0143*** (3.965), and 0.0150*** (4.602) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.00155	0.0132***	0.00186*	0.0161***	0.00193*	0.0169***
	(1.346)	(4.755)	(1.679)	(6.066)	(1.921)	(7.072)
Observations	2,367	8,466	2,367	8,466	2,367	8,466
R-squared	0.838	0.634	0.838	0.635	0.838	0.635
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Brown industry indicator as main regressor

The table shows how our main result is robust to different proxy for firms' greenness. In particular, compared to our benchmark case (Table 2), we use brown industry indicator as main regressor. The indicator is set 1 if two-digit SIC code's CO2 emission is above the median. Otherwise, it is sets to 0. (1), (3), and (5) report the results when the model is estimated on the primary market whereas (2), (4), and (6) report the results estimated on the secondary market. (1) and (2) report the results when Scope 1 and 2 intensity measure is used whereas (3) and (4) ((5) and (6)) report the results when Scope 1 (Scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 2.025*** (14.86), 0.850*** (10.70), and 1.759*** (13.39) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
Brown industry indicator	0.214***	2.239***	0.0210	0.871***	0.181***	1.940***
	(4.695)	(27.36)	(0.868)	(15.85)	(4.204)	(23.90)
Observations	2,563	9,025	2,563	9,025	2,563	9,025
R-squared	0.845	0.629	0.843	0.609	0.844	0.623
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Different subsamples based on time

The table shows how our main result is robust to different time-series subsample. Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when Scope 1 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when Scope 1 and 2 (Scope 1,2, and 3) is used.

Panel A1 shows the estimates for 2005-2013 period. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.00970 (1.300), 0.0157** (2.265), and 0.0149** (2.360) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

Panel A2 shows the estimates for 2014-2022 period. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.00718** (2.337), 0.00769** (2.530) , and 0.00886*** (3.174) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

Panel B1 shows the estimates for odd years. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.0149*** (2.892), 0.0185*** (3.752), and 0.0176*** (4.014) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

Panel B2 shows the estimates for even years. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.00953** (2.203), 0.00995** (2.352), and 0.0106*** (2.680) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
Panel A1: 2005-2013						
CO2	0.00637**	0.0161***	0.00514**	0.0208***	0.00484**	0.0197***
	(2.560)	(3.053)	(2.222)	(4.253)	(2.296)	(4.429)
Observations	749	3,306	749	3,306	749	3,306
R-squared	0.831	0.674	0.831	0.675	0.831	0.675
Panel A2: 2014-2022						
CO2	-0.00160	0.00559**	-0.000984	0.00670***	-0.000687	0.00817***
	(-1.494)	(2.444)	(-0.933)	(2.958)	(-0.706)	(3.946)
Observations	1,679	5,219	1,679	5,219	1,679	5,219
R-squared	0.856	0.642	0.856	0.642	0.856	0.643
Panel B1: Odd Years						
CO2	0.00441**	0.0193***	0.00429***	0.0227***	0.00398***	0.0216***
	(2.543)	(5.218)	(2.583)	(6.436)	(2.693)	(6.862)
Observations	1,162	4,322	1,162	4,322	1,162	4,322
R-squared	0.832	0.555	0.832	0.557	0.832	0.557
Panel B2: Even Years						
CO2	0.000548	0.0101***	0.000872	0.0108***	0.000947	0.0115***
	(0.415)	(3.126)	(0.677)	(3.416)	(0.782)	(3.925)
Observations	1,265	4,203	1,265	4,203	1,265	4,203
R-squared	0.858	0.705	0.858	0.705	0.858	0.705
Bond/Firm controls	YES	YES	YES	YES	YES	YES
FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Absolute CO2 emissions

The table shows that our main result is robust to different definition of CO2 emission: total CO2 emission. Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when Scope 1 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when Scope 1 and 2 (Scope 1,2, and 3) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.0428*** (3.723), 0.0527*** (3.275) , and 0.101*** (4.208) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.00705*	0.0499***	0.0121**	0.0649***	0.0157**	0.117***
	(1.831)	(6.378)	(2.274)	(5.831)	(1.979)	(6.981)
Observations	2,428	8,525	2,428	8,525	2,428	8,525
R-squared	0.839	0.630	0.839	0.630	0.839	0.630
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10: Robustness: Liquidity risk

Table shows that bond spreads' sensitivity to CO2 intensity on the secondary market does not depend on the days we use to measure spreads, whether it is on the day of the issuance or on the days just before and after the issuance. In order to show this, we estimate Equation 1 for days just before and just after a given firm issues a new bond. Columns (2), (4) and (6) include our estimation results. Columns (1), (3), and (5) reproduce the estimates obtained when secondary market spreads are measured on the day of the issuance, as they appear in Table 2.
When Scope 1 is used, column (2) is not statistically different from column (1) (t-test: 0.10). When Scope 1 and 2 is used, column (4) is not statistically different from column (3) (t-test: 0.37). When Scope 1, 2, and 3 is used, column (6) is not statistically different from column (5) (t-test: 0.41).

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
CO2	0.0158***	0.0155***	0.0180***	0.0169***	0.0183***	0.0172***
	(6.514)	(8.466)	(7.632)	(9.586)	(8.543)	(10.75)
Observations	8,525	15,693	8,525	15,693	8,525	15,693
R-squared	0.630	0.568	0.631	0.568	0.631	0.569
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Robustness: More precise definition of CO2 emission

The table shows that our main result is robust to different precision levels of CO2 emission definitions. Precision level classifications are in Table A11. The description of results are similar to what is described in Table 9.
Panel A focus on the sample with precision level 4 or above. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.0133*** (4.050), 0.0153*** (4.789), and 0.0157*** (5.400) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.
Panel B focus on the sample with precision level 5. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.0140*** (4.330), 0.0159*** (5.078), and 0.0163*** (5.696) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
Panel A: Precision level 4 or above						
CO2	0.00234**	0.0157***	0.00252**	0.0178***	0.00245***	0.0182***
	(2.257)	(6.443)	(2.521)	(7.544)	(2.663)	(8.474)
Observations	2,404	8,506	2,404	8,506	2,404	8,506
R-squared	0.841	0.631	0.841	0.631	0.841	0.632
Panel B: Precision level 5						
CO2	0.00227**	0.0163***	0.00247**	0.0184***	0.00240***	0.0187***
	(2.170)	(6.785)	(2.444)	(7.900)	(2.589)	(8.844)
Observations	2,353	8,102	2,353	8,102	2,353	8,102
R-squared	0.841	0.648	0.841	0.648	0.841	0.649
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: Channel: Uncertainty

Table tests uncertainty channel. We first construct HV_t where HV_t proxies the uncertainty of future climate concerns at time t. For this, we use daily Media Climate Change Concerns index that was constructed and was made available to download by Ardia et al. (2022). We use ARCH model to estimate the conditional volatility at day t conditioned on all the daily data between $t-1$ and $t-30$. Then, we set $HV_t = 1$ if the measure is above the median. Otherwise, we set it to 0. Then, we estimate the following model:

$$\begin{aligned} Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot HV_t + \beta_3 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\ &+ \beta_4 \cdot CO2_{f,t} \times HV_t + \beta_5 \cdot Secondary_{f,i,t} \times HV_t + \beta_6 \cdot Secondary_{f,i,t} \times CO2_{f,t} \times HV_t \\ &+ BondCtrl_{f,i,t} + Secondary_{f,i,t} \times BondCtrl_{f,i,t} + FirmCtrl_{f,t} \\ &+ Secondary_{f,i,t} \times FirmCtrl_{f,t} + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned}$$

where $Spread_{f,i,t}$ is spread of the bond i that is issued at time t by firm f. Table reports the estimates of β's.

	(1) Scope 1	(2) Scope 1 and 2	(3) Scope 1,2, and 3
CO2	0.00186	0.00178	0.00221
	(0.524)	(0.522)	(0.704)
HV	-0.0310	-0.0312	-0.0314
	(-0.953)	(-0.961)	(-0.962)
CO2 X Secondary	0.00977**	0.0131***	0.0131***
	(2.069)	(2.895)	(3.156)
CO2 X HV	0.00734	0.00693	0.00464
	(1.293)	(1.286)	(0.970)
HV X Secondary	-0.0517	-0.0510	-0.0487
	(-1.424)	(-1.402)	(-1.334)
CO2 X Secondary X HV	0.0258***	0.0222***	0.0204***
	(3.343)	(3.033)	(3.207)
Observations	8,495	8,495	8,495
R-squared	0.662	0.663	0.664
Bond controls	YES	YES	YES
Firm controls	YES	YES	YES
Bond controls X Secondary	YES	YES	YES
Firm controls X Secondary	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Month FE	YES	YES	YES
DOW FE	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES
Industry X Secondary FE	YES	YES	YES
Year X Secondary FE	YES	YES	YES
Month X Secondary FE	YES	YES	YES
DOW X Secondary FE	YES	YES	YES
LeadUnderwriter1-10 X Secondary FE	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13: Channel: Competition among underwriters

Table tests competition channel. We first construct $LC_{f,i}$ where it proxies the degree of competition among the lead underwriters for the bond i that is issued by firm f. We define

$$Ratio = \frac{\text{Number of lead underwriters}}{\text{Amount offered}}$$

And we set $LC_{f,i} = 1$ if the ratio is below the median. Otherwise, we set it to 0. Then, we estimate the following:

$$\begin{aligned} Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot LC_{f,i} + \beta_3 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\ &+ \beta_4 \cdot CO2_{f,t} \times LC_{f,i} + \beta_5 \cdot Secondary_{f,i,t} \times LC_{f,i} + \beta_6 \cdot Secondary_{f,i,t} \times CO2_{f,t} \times LC_{f,i} \\ &+ BondCtrl_{f,i,t} + Secondary_{f,i,t} \times BondCtrl_{f,i,t} + FirmCtrl_{f,t} \\ &+ Secondary_{f,i,t} \times FirmCtrl_{f,t} + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned}$$

$Spread_{f,i,t}$ is spread of the bond i that is issued at time t by firm f. Table reports the estimates for β's.

	(1) Scope 1	(2) Scope 1 and 2	(3) Scope 1,2, and 3
CO2	0.00259	0.00269	0.00295
	(0.623)	(0.658)	(0.767)
LC	0.0175	0.0172	0.0178
	(0.351)	(0.342)	(0.346)
CO2 X Secondary	0.00767	0.00745	0.00788
	(1.395)	(1.382)	(1.560)
CO2 X LC	0.00334	0.00257	0.00162
	(0.603)	(0.483)	(0.326)
LC X Secondary	0.0548	0.0451	0.0311
	(0.903)	(0.741)	(0.498)
CO2 X Secondary X LC	0.0213***	0.0251***	0.0232***
	(2.831)	(3.510)	(3.507)
Observations	8,495	8,495	8,495
R-squared	0.661	0.662	0.663
Bond controls	YES	YES	YES
Firm controls	YES	YES	YES
Bond controls X Secondary	YES	YES	YES
Firm controls X Secondary	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Month FE	YES	YES	YES
DOW FE	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES
Industry X Secondary FE	YES	YES	YES
Year X Secondary FE	YES	YES	YES
Month X Secondary FE	YES	YES	YES
DOW X Secondary FE	YES	YES	YES
LeadUnderwriter1-10 X Secondary FE	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Internet Appendix for

"Do carbon emissions affect the cost of capital? Primary versus secondary corporate bond markets"

by Daniel Kim and Sébastien Pouget

A A simple model

To elucidate the potential drivers of our main results, we set up a model, in spirit of Gollier and Pouget (2022). Our model is very stylized but it can rationalize the fact that the carbon premium is lower on the primary than on the secondary market and it points to the two potential channels that we study, namely the uncertainty and competition channels.

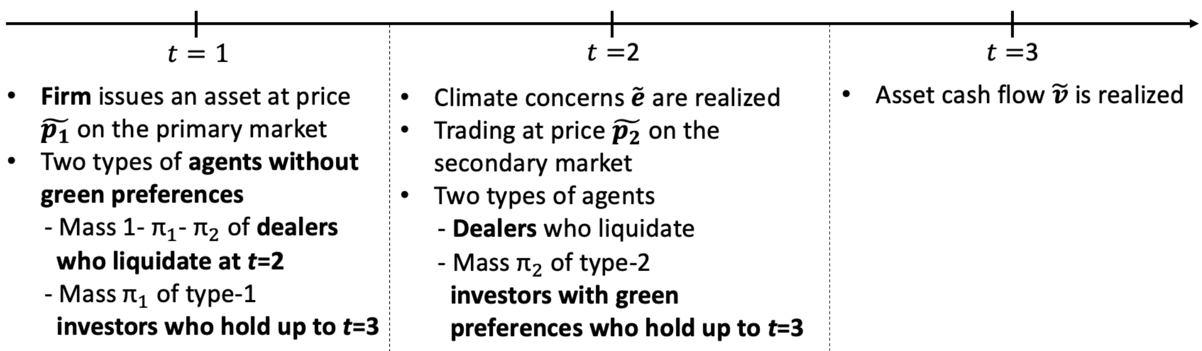


Figure A1: Timeline for the model

Our model includes three dates as illustrated in Figure A1. At date 1, the firm issues assets on the primary market, at price $\tilde{p}_1$, for an amount normalized to 1. Underwriting dealers trade on the primary market at date 1 and liquidate their position on the secondary market at date 2, at price $\tilde{p}_2$. They form a continuum of mass $1-\pi$ with $0 < \pi \leq 1$. Investors buy and hold the assets up to date 3. There are two types of investors. Type-1 investors form a continuum of mass π_1 and buy at date 1. Type-2 investors form a continuum of mass π_2, with $\pi_1 + \pi_2 = \pi$, and buy at date 2. At date 3, assets mature and deliver a financial cash flow denoted by $\tilde{v}$, normally distributed with mean μ_v and variance σ_v^2. At date 3, the firm also generates carbon emissions inducing a climate change externality.

We assume that all agents in our model have a constant relative risk aversion utility function with parameter A. They have the following mean-variance objective: $\max_{q_i} \mathbb{E}(\tilde{w}_i(q_i)) - \frac{A}{2} \cdot \mathbb{V}(\tilde{w}_i(q_i))$, in which q_i represents the quantity traded by agent i, positive for a purchase and negative for a sale, and $\tilde{w}_i(q_i)$ is agent i's final wealth. We can write an agent's objective as a mean-variance optimization program because, as will become clear later, $\tilde{w}_i(q_i)$ is normally distributed.

Agents have no endowment in assets nor in cash and can borrow or lend at the risk-free rate that is normalized to 0. For a dealer, we have $\tilde{w}_d = q_d(\tilde{p}_2 - \tilde{p}_1)$; for a type-1 investor, we have $\tilde{w}_1 = q_1(\tilde{v} - \tilde{p}_1)$. Type-2 investors care about the climate externality and we assume that $\tilde{w}_2 = q_2(\tilde{v} + \tilde{e} - \tilde{p}_2)$.[27] The variable $\tilde{e}$, normally distributed with mean μ_e and variance σ_e^2, represents how much type-2 investors care about the climate externality. When they trade, agents submit limit orders and thus can condition on the current price. The random variable $\tilde{e}$ is realized just before trading at date 2.[28] A a result, in our model, the correlation between $\tilde{v}$ and $\tilde{e}$ is irrelevant.

We are agnostic regarding the reason(s) why type-2 investors care about the externality. They might enjoy a warm-glow or a reputational benefit for holding assets of a firm with a good climate performance, either in relative terms (i.e., a firm with a low carbon intensity), or in absolute terms (i.e., a firm with low carbon emissions). In this case, $\tilde{e}$ enters the utility function because investors internalize the good environmental impact of the firm relative to more polluting firms (see also, e.g., Pastor, Stambaugh, and Taylor (2021)). Alternatively, type-2 investors might believe that a firm with a good climate performance enjoys an additional return materialized by $\tilde{e}$.

Given these ingredients, we solve the model backward. At date 2, on the secondary market, each type-2 investor demands a quantity $q_2 = \frac{\mu_v + e - p_2}{A\sigma_v^2}$.[29] The supply at this date derives from

[27] We could consider that type-1 investors also care about the climate externality, potentially with a different intensity than type-2 investors. In this case, our results would hold as long as type-1 investors' climate concerns are less intense than type-2 investors' ones.

[28] We thus assume that type-2 investors are able to perceive whether the firm's operations are more or less polluting before learning about the profitability of these operations.

[29] We write random variables with a tilde and their realisation without a tilde.

dealers who liquidate their position: this amounts to $(1-\pi)q_d$. Market clearing at date 2 is ensured if $\pi_2 q_2 = (1-\pi)q_d$ which yields the implicit secondary market price: $p_2 = \mu_v + e - \frac{1-\pi}{\pi_2} q_d A\sigma_v^2$.

At date 1, on the primary market, type-1 investors demand a quantity $q_1 = \frac{\mu_v - p_1}{A\sigma_v^2}$ since they hold the asset up to maturity. A dealer's maximization problem depends on the aggregate quantity that will be traded by dealers at date 2 denoted by $(1-\pi)q'_d$. A dealer's optimal trade at date 1 is thus: $q_d = \frac{\mu_v + \mu_e - \frac{1-\pi}{\pi_2} q'_d A\sigma_v^2 - p_1}{A\sigma_e^2}$. Rational expectations entail that $q_d = q'_d$. So we have: $q_d = \frac{\mu_v + \mu_e - p_1}{A(\sigma_e^2 + \frac{1-\pi}{\pi_2}\sigma_v^2)}$. The market-clearing equation at date 1 is $(1-\pi)q_d + \pi_1 q_1 = 1$ which yields the explicit primary price: $p_1 = \mu_v + \frac{X}{X+Y}\mu_e - \frac{1}{X+Y}$, with $X = \frac{1-\pi}{A(\sigma_e^2 + \frac{1-\pi}{\pi_2}\sigma_v^2)}$ and $Y = \frac{\pi_1}{A\sigma_v^2}$.

Given this price p_1, we obtain $q_d = \frac{X + XY\mu_e}{(1-\pi)(X+Y)}$ and plug it into the secondary market price equation to obtain the explicit formula: $p_2 = \mu_v + e - \frac{\pi_1}{\pi_2}\frac{X + XY\mu_e}{XY + Y^2}$. From an econometric point of view, we are interested in the average secondary market price: $\mathbb{E}(p_2) = \mu_v + \mu_e - \frac{\pi_1}{\pi_2}\frac{X + XY\mu_e}{XY + Y^2}$.

We can now derive our main result regarding the sensitivity of prices to investors' climate change concerns measured by μ_e. Our analysis shows that $\frac{\partial p_1}{\partial \mu_e} = \frac{X}{X+Y}$ and $\frac{\partial \mathbb{E}(p_2)}{\partial \mu_e} = 1 - \frac{\pi_1}{\pi_2}\frac{XY}{XY+Y^2}$. Both of these partial derivatives are greater than 0 and smaller than 1, and we have $\frac{\partial \mathbb{E}(p_2)}{\partial \mu_e} - \frac{\partial p_1}{\partial \mu_e} = \frac{\pi_1 \pi_2 \sigma_e^2}{\pi_1 \pi_2 \sigma_e^2 + \pi(1-\pi)\sigma_v^2}$. When $\pi_1 \pi_2 \sigma_e^2 > 0$, the sensitivity of prices to climate change concerns is thus larger on the secondary than on the primary market. This rationalizes our main empirical result.

The intuition for this main result is as follows. Type-2 investors care about climate change but they do not participate in the primary market. Their concerns are incorporated in the primary market price only thanks to dealers' participation. Because they liquidate their position on the secondary market, dealers try to predict the price at which they will trade which depends on type-2 investors' climate concerns. However, the primary market price does not only reflect dealers' trades, it also incorporates type-1 investors' views. As long as these investors care less about climate change than type-2 investors, the primary price will be less sensitive to climate change concerns than the secondary market price.

To point towards our first potential uncertainty channel, we note that $\frac{\partial \frac{\partial \mathbb{E}(p_2)}{\partial \mu_e} - \frac{\partial p_1}{\partial \mu_e}}{\partial \sigma_e} > 0$. Thus, when uncertainty regarding climate change concerns is higher, there is a higher difference between sensitivities on the secondary and on the primary market than when uncertainty is low.

The intuition for this result is that, when there is more uncertainty about type-2 investors climate concerns, dealers are trading less aggressively on the primary market and thus their views, which depend on their expectation of type-2 investors climate concerns, have less influence on the price. As a result, the more uncertainty on climate concerns there is, the less aggressive dealers trade and the less climate change concerns are incorporated into the primary market price.

To point towards our second potential competition channel, we slightly modify our set up and assume that there is only one dealer with weight $1-\pi$ on the market. The dealer who knows that liquidation at date 2 will affect prices maximizes $q_d(\mu_v + \mu_e - \frac{1-\pi}{\pi_2} q_d A \sigma_v^2 - p_1) - \frac{A}{2} q_d^2 \sigma_e^2$. Dealer's demand is thus $q_d = \frac{\mu_v + \mu_e - p_1}{A(\sigma_e^2 + 2\frac{1-\pi}{\pi_2}\sigma_v^2)}$. All results we obtained previously hold by replacing X by $X' = \frac{1-\pi}{A(\sigma_e^2 + 2\frac{1-\pi}{\pi_2}\sigma_v^2)} < X$. We thus have that the difference in sensitivities is now equal to: $\frac{\partial \mathbb{E}(p_2)}{\partial \mu_e} - \frac{\partial p_1}{\partial \mu_e} = \frac{\pi_1 \pi_2 \sigma_e^2 + \pi_1(1-\pi)\sigma_v^2}{\pi_1 \pi_2 \sigma_e^2 + \pi(1-\pi)\sigma_v^2 + \pi_1(1-\pi)\sigma_v^2}$. This is greater than the difference in sensitivity when there is perfect competition. Thus there is a higher difference between secondary and primary market sensitivity when there is low competition among dealers.

The intuition of this result is that, when there is less competition on the primary market, dealers are trading less aggressively. As before, this implies that their views, which depend on their expectation of type-2 investors climate concerns, have less influence on the primary price.

B More Robustness Check

We run a variety of additional robustness tests for our main results.

B.1 Additional lag

We start by using a different lag for our main explanatory variable. As mentioned in Section 3, our main regressor, $CO2_{f,t}$, is firm f's latest carbon intensity measure available at time t. In our main analysis, we consider that CO2 data are made available to financial market participants at the same time as accounting data: we lag CO2 emissions by one year as we do with accounting variables, i.e., we use emissions and accounting figures as of the end of the previous fiscal year.

However, as indicated by Zhang (2023), CO2 emissions data might suffer from longer reporting lags than accounting data. In order to test whether this concern affects our results, we lag our CO2 emissions measure (and the associated sales figure that scales it) by one additional year compared to accounting variables. Our main results stay robust to this alternative specification.

Table A1: Robustness: Additional lags

The table shows how our main result is robust to lagging CO2 emission measure by one extra year. Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when Scope 1 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when Scope 1 and 2 (Scope 1,2, and 3) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.0121*** (3.844), 0.0138*** (4.544) , and 0.0140*** (5.063) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.00288***	0.0149***	0.00286***	0.0166***	0.00274***	0.0167***
	(2.927)	(6.411)	(3.004)	(7.383)	(3.154)	(8.175)
Observations	2,428	8,525	2,428	8,525	2,428	8,525
R-squared	0.839	0.630	0.839	0.631	0.839	0.631
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.2 Different Winsorizations

As mentioned in Section 2.3, in our main analysis, we winsorize all our variables at 1% level. Even though a 1%-winsorization level is a well-accepted practice in the literature, there is no particular reason to use this rather than another level. We thus study how our main results depend on the level of winsorization by running our main specification without any winsorization and with a 2.5%-winsorization level.

Our main result appears robust to different winsorization levels but there is some sign of outliers that would have affected our estimates absent winsorization. Indeed, focusing on the sum of Scope 1, 2 and 3 emissions, spread sensitivity to carbon intensity appears larger on the secondary than on the primary market for all levels of winsorization but the size and statistical significance of this effect increases with the level of winsorization. A similar pattern arises when other Scopes of emissions are used.

Table A2: Robustness: Winsorization

The table shows how our main result is robust to different levels of winsorization: no winsorization or 2.5% winsorization on both ends. Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when Scope 1 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when Scope 1 and 2 (Scope 1,2, and 3) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Panel A shows a case where data are not winsorized. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.00927*** (3.408), 0.0108*** (4.105), and 0.0114*** (4.707) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

Panel B shows a case when data are winsorized at 2.5% for both ends. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.0226*** (4.752), 0.0242*** (5.550), and 0.0231*** (6.073) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
Panel A: No winsorization						
CO2	0.00171**	0.0110***	0.00180**	0.0126***	0.00177**	0.0132***
	(2.041)	(5.381)	(2.238)	(6.366)	(2.365)	(7.252)
Observations	2,428	8,525	2,428	8,525	2,428	8,525
R-squared	0.845	0.631	0.845	0.632	0.845	0.632
Panel B: 2.5% winsorization on both ends						
CO2	0.00412***	0.0267***	0.00427***	0.0285***	0.00394***	0.0270***
	(2.688)	(7.767)	(3.036)	(9.004)	(3.201)	(9.851)
Observations	2,428	8,525	2,428	8,525	2,428	8,525
R-squared	0.835	0.627	0.836	0.628	0.836	0.628
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.3 More granular fixed effects

Our main specification controls for industry-level effects at the one-digit SIC code level inducing 9 different broad industries. When we interact industry fixed effects with year, our results are qualitatively and quantitatively similar. This suggests that bond market participants account for possible different time series industry-wide variation in comparing firms' carbon intensity across firms within industry category.

When we run our main specification by controlling instead for two-digit SIC code industry fixed effects associated in our data with 59 industrial categories, our results are qualitatively and quantitatively similar. This suggests that bond market participants compare firms' carbon intensity across firms not only within broad industries but also within smaller industrial categories.

When we include firm fixed effects (in untabulated results), our main result does not hold. This indicates that bond market participants tend to pay more attention to cross-sectional than to time-series differences in carbon intensity. This is consistent with the literature's practice that applies fixed effects only at the industry level.

Table A3: Robustness: Different industry fixed effects

The table shows how our main results vary over different industry fixed effects in place of one-digit SIC industry fixed effects. Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when Scope 1 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when Scope 1 and 2 (Scope 1,2, and 3) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Panel A shows a case where we apply 1 digit SIC code industry interacted with year fixed effects. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.0148*** (4.448), 0.0164*** (5.082), and 0.0165*** (5.590) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

Panel B shows a case where we apply 2-digit SIC code industry fixed effects. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.00441 (0.937), 0.00919** (2.012), and 0.0108** (2.532) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
Panel A: (One digit SIC industry) X (Year) FE						
CO2	0.00204*	0.0168***	0.00233**	0.0187***	0.00246***	0.0190***
	(1.912)	(6.873)	(2.251)	(7.870)	(2.593)	(8.739)
Observations	2,420	8,518	2,420	8,518	2,420	8,518
R-squared	0.848	0.656	0.849	0.657	0.849	0.657
Panel B: Two digit SIC industry FE						
CO2	-0.00158	0.00283	-0.00139	0.00781**	-0.00110	0.00971***
	(-1.120)	(0.779)	(-1.012)	(2.212)	(-0.852)	(2.960)
Observations	2,426	8,522	2,426	8,522	2,426	8,522
R-squared	0.846	0.638	0.846	0.638	0.846	0.638
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.4 Data filters

In constructing our main data set, as discussed in Section 2, we restricted data to consider senior bonds with carbon emission precision level 2 or above. We run our analysis without these two filters and find that spread sensitivity to CO2 emission on the secondary market is around three and a half times larger than that on the primary market. The unfiltered sample contains 355 unique firms as opposed to 219 unique firms in our benchmark sample. This suggests that, in our analysis, neither the precision issue highlighted by Aswani et al. (2023a) nor bond seniority are driving our main results.

Table A4: Robustness: Less data filter

The table shows how our main result is robust to different data filters implied. In particular, compared to our benchmark case (Table 2), we do not impose two data filters: bonds with senior seniority and bonds with precision level 2 or above, and we include seniority FE. (1), (3), and (5) report the results when the model is estimated on the primary market whereas (2), (4), and (6) report the results estimated on the secondary market. (1) and (2) report the results when Scope 1 and 2 intensity measure is used whereas (3) and (4) ((5) and (6)) report the results when Scope 1 (Scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.00988*** (4.257), 0.0112*** (4.952), and 0.0111*** (5.325) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	-0.000686	0.00920***	-0.000461	0.0107***	-0.000593	0.0105***
	(-0.878)	(5.701)	(-0.607)	(6.816)	(-0.845)	(7.228)
Observations	4,788	17,459	4,788	17,459	4,788	17,459
R-squared	0.812	0.559	0.812	0.560	0.812	0.560
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.5 Secondary market transaction

Table A5: Robustness: All secondary market transaction

This includes all the secondary market transactions as opposed to focusing only on the transactions that happened within two years since the issuance. Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.0142*** (4.009), 0.0164*** (4.943), and 0.0158*** (5.232) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.00118	0.0153***	0.00125	0.0176***	0.00122	0.0170***
	(1.285)	(8.048)	(1.467)	(9.652)	(1.563)	(10.33)
Observations	3,009	22,626	3,009	22,626	3,009	22,626
R-squared	0.847	0.671	0.847	0.671	0.847	0.671
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.6 “On-the-run” bonds

Our main result is robust to matching primary market bonds to the secondary market prices of the on-the-run bonds. In this analysis, we compare primary market bond pricing to the secondary market pricing of the most recently issued bond of the same issuer.

Table A6: Robustness: On-the-run bonds

The table shows how our main result is robust to matching primary market bonds to the secondary market prices of the on-the-run bonds. In particular, compared to our benchmark case (Table 2), for each primary market bond, we keep the same issuers' secondary market prices of the most recently issued bonds as of the primary market bond issuance. (1), (3), and (5) report the results when the model is estimated on the primary market whereas (2), (4), and (6) report the results estimated on the secondary market. (1) and (2) report the results when Scope 1 and 2 intensity measure is used whereas (3) and (4) ((5) and (6)) report the results when Scope 1 (Scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.0116*** (3.814), 0.0140*** (4.761), and 0.0138*** (5.114) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.00251**	0.0142***	0.00273***	0.0168***	0.00267***	0.0165***
	(2.418)	(4.539)	(2.723)	(5.569)	(2.901)	(5.969)
Observations	2,428	1,938	2,428	1,938	2,428	1,938
R-squared	0.839	0.534	0.839	0.536	0.839	0.537
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.7 Nonlinear relation

The relation between CO2 and the bond spread could be nonlinear. We show that our main result is robust to additionally controlling for nonlinear term: CO2 squared.

Table A7: Robustness: CO2 squared as additional control

The table shows how our main result is robust to controlling for the nonlinear relation between CO2 and the outcome variable. In particular, compared to our benchmark case (Table 2), we additionally control for CO2 squared. (1), (3), and (5) report the results when the model is estimated on the primary market whereas (2), (4), and (6) report the results estimated on the secondary market. (1) and (2) report the results when Scope 1 and 2 intensity measure is used whereas (3) and (4) ((5) and (6)) report the results when Scope 1 (Scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + \gamma \cdot CO2^2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Using Equation (2), the difference in β_1 between the primary market and secondary market are estimated as 0.0484*** (4.881), 0.0532*** (5.533), and 0.0464*** (5.186) respectively for Scope 1 intensity, Scope 1 and 2 intensity, and Scope 1,2,3 intensity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1		Scope 1 and 2		Scope 1, 2, and 3	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.00512	0.0536***	0.00743**	0.0606***	0.00595**	0.0524***
	(1.613)	(7.407)	(2.426)	(8.609)	(2.070)	(8.061)
CO2 X CO2	-6.72e-05	-0.00102***	-0.000118	-0.00113***	-7.68e-05	-0.000844***
	(-0.870)	(-5.538)	(-1.624)	(-6.423)	(-1.204)	(-5.554)
Observations	2,428	8,525	2,428	8,525	2,428	8,525
R-squared	0.839	0.631	0.839	0.633	0.839	0.633
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.8 Robustness: Competition among underwriters

Table A8: Robustness: Channel - Competition among underwriters

Table tests competition channel. We first construct $LC_{f,i}$ where it proxies the degree of competition among the lead underwriters for the bond i that is issued by firm f. We take average of underwriters' competitiveness using measures proposed by Manconi et al. (2019). Then, we set $LC_{f,i} = 1$ if the average is below the median. Otherwise, we set it to 0. Then, we estimate the following:

$$\begin{aligned}
Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot LC_{f,i} + \beta_3 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\
&+ \beta_4 \cdot CO2_{f,t} \times LC_{f,i} + \beta_5 \cdot Secondary_{f,i,t} \times LC_{f,i} + \beta_6 \cdot Secondary_{f,i,t} \times CO2_{f,t} \times LC_{f,i} \\
&+ BondCtrl_{f,i,t} + Secondary_{f,i,t} \times BondCtrl_{f,i,t} + FirmCtrl_{f,t} \\
&+ Secondary_{f,i,t} \times FirmCtrl_{f,t} + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t}
\end{aligned}$$

$Spread_{f,i,t}$ is spread of the bond i that is issued at time t by firm f. Table reports the estimates for β's.

	(1) Scope 1	(2) Scope 1 and 2	(3) Scope 1,2, and 3
CO2	0.00168	0.00169	0.00231
	(0.283)	(0.294)	(0.432)
LC	-0.0884	-0.0891	-0.0906
	(-1.162)	(-1.173)	(-1.173)
CO2 X Secondary	0.0198**	0.0187**	0.0191**
	(2.326)	(2.281)	(2.557)
CO2 X LC	0.00896	0.00780	0.00578
	(1.055)	(0.967)	(0.797)
LC X Secondary	-0.110	-0.104	-0.100
	(-1.290)	(-1.214)	(-1.158)
CO2 X Secondary X LC	0.0280**	0.0389***	0.0279***
	(2.295)	(3.410)	(2.812)
Observations	6,403	6,403	6,403
R-squared	0.678	0.681	0.681
Controls	YES	YES	YES
Controls X Secondary	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Month FE	YES	YES	YES
DOW FE	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES
Industry X Secondary FE	YES	YES	YES
Year X Secondary FE	YES	YES	YES
Month X Secondary FE	YES	YES	YES
DOW X Secondary FE	YES	YES	YES
LeadUnderwriter1-10 X Secondary FE	YES	YES	YES

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.9 Robustness: Uncertainty and Competition among underwriters

Table A9: Robustness: Channel - Uncertainty and Competition among underwriters

Table tests both uncertainty and competition channel. We construct HV_t as in Table 12 and $LC_{f,i}$ as in Table 13. Then, we estimate the following:

$$\begin{aligned} Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot HV_t + \beta_3 \cdot LC_t + \beta_4 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\ &+ \beta_5 \cdot CO2_{f,t} \times HV_t + \beta_6 \cdot Secondary_{f,i,t} \times HV_t + \beta_7 \cdot Secondary_{f,i,t} \times CO2_{f,t} \times HV_t \\ &+ \beta_8 \cdot CO2_{f,t} \times LC_{f,i} + \beta_9 \cdot Secondary_{f,i,t} \times LC_{f,i} + \beta_1 0 \cdot Secondary_{f,i,t} \times CO2_{f,t} \times LC_{f,i} \\ &+ BondCtrl_{f,i,t} + FirmCtrl_{f,t} + FE + \varepsilon_{f,i,t} \end{aligned}$$

$Spread_{f,i,t}$ is spread of the bond i that is issued at time t by firm f. Table reports the estimates for β's.

	(1) Scope 1	(2) Scope 1 and 2	(3) Scope 1,2, and 3
CO2	-0.000215	4.70e-05	0.00113
	(-0.0466)	(0.0104)	(0.266)
LC	0.0162	0.0155	0.0168
	(0.325)	(0.309)	(0.325)
HV	-0.0325	-0.0326	-0.0328
	(-1.002)	(-1.005)	(-1.005)
CO2 X Secondary	-0.0101	-0.00899	-0.00573
	(-1.597)	(-1.460)	(-1.006)
CO2 X LC	0.00413	0.00325	0.00207
	(0.745)	(0.612)	(0.418)
LC X Secondary	0.0558	0.0450	0.0281
	(0.923)	(0.743)	(0.452)
CO2 X Secondary X LC	0.0350***	0.0376***	0.0318***
	(4.545)	(5.135)	(4.743)
CO2 X HV	0.00764	0.00711	0.00468
	(1.344)	(1.319)	(0.978)
HV X Secondary	-0.0449	-0.0433	-0.0414
	(-1.238)	(-1.194)	(-1.137)
CO2 X Secondary X HV	0.0397***	0.0365***	0.0299***
	(5.010)	(4.877)	(4.619)
Observations	8,495	8,495	8,495
R-squared	0.665	0.666	0.666
Controls	YES	YES	YES
Controls X Secondary	YES	YES	YES
FE	YES	YES	YES
Secondary X FE	YES	YES	YES

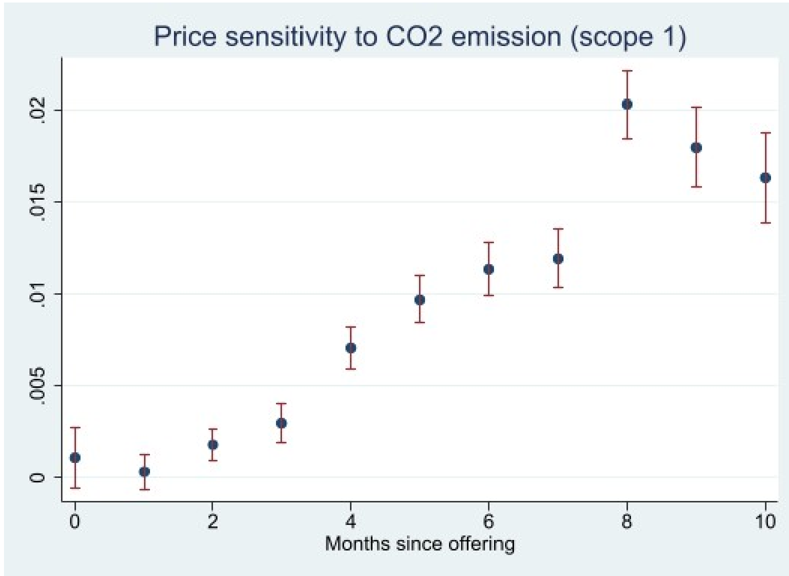
Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.10 More time-series analysis

Table A10: Summary statistics for time series analysis

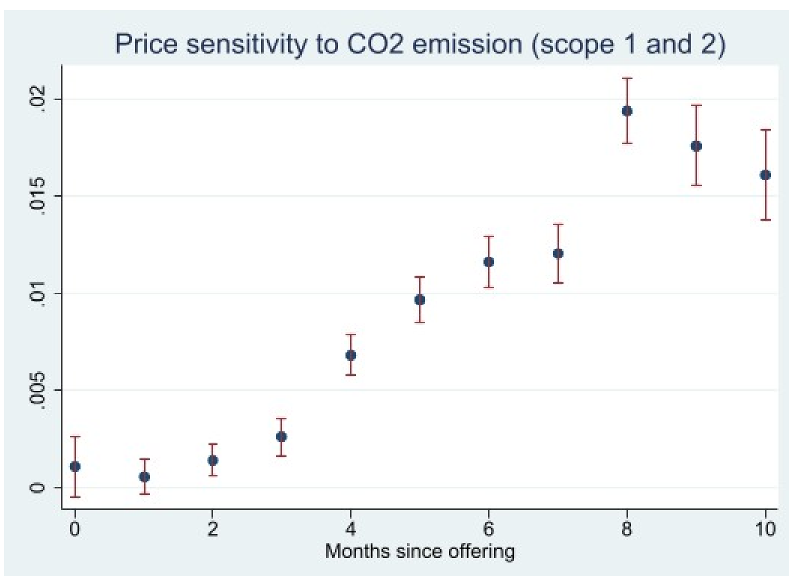
Table show summary statistics for the sample that are used in our time series analysis (see Section 4.1). Our data sample covers 3,237 bond issues from 302 unique US firms. The sample spans from 2005 to 2022. We winsorize all the variables at top and bottom 1%. Variable definitions are similar to what is described in Table 1.

	N	Mean	SD	Median
CO2 emission measures				
Log(Carbon Emission Scope 1 (tons CO2e))	302	12.61	2.617	12.61
Log(Carbon Emission Scope 1 and 2 (tons CO2e))	302	13.93	1.959	13.89
Log(Carbon Emission Scope 1, 2, and 3 (tons CO2e))	302	15.31	1.501	15.47
Carbon intensity Scope 1 (tons CO2e/USD m.)/100	302	2.502	7.277	0.0917
Carbon intensity Scope 1 and 2 (tons CO2e/USD m.)/100	302	2.967	7.652	0.373
Carbon intensity Scope 1, 2, and 3 (tons CO2e/USD m.)/100	302	4.623	8.355	1.648
Firm characteristics				
Book leverage	302	0.306	0.160	0.288
Interest coverage ratio	302	0.113	0.127	0.0817
Firm size	302	10.96	1.570	10.65
ROA	302	0.138	0.0913	0.136
Firm sale	302	10.12	1.097	10.04
Equity return mean	302	0.115	0.263	0.142
Log(Equity return vol)	302	-1.558	0.438	-1.575
Bond characteristics				
Offering spread (%)	3,237	0.674	0.629	0.492
Secondary spread (%)	3,237	0.524	0.943	0.421
Number of lead underwriters	3,237	2.788	1.227	3
Number of all underwriters	3,237	5.398	1.126	6
Illiquidity	3,237	0.0180	0.252	0.000760
Rating (Moody's)	3,237	15.05	2.665	15
$\mathbb{1}\{$Redeemable$\}$	3,237	0.916	0.278	1
Years to maturity	3,237	11.98	9.979	9.534
Amount outstanding (thousands)	3,237	1.084e+06	746,929	943,696
Coupon (%)	3,237	3.473	1.396	3.350
$\mathbb{1}\{$Lead underwritten by J.P. Morgan$\}$	3,237	0.414	0.493	0
$\mathbb{1}\{$Lead underwritten by Citi$\}$	3,237	0.359	0.480	0
$\mathbb{1}\{$Lead underwritten by Merrill Lynch$\}$	3,237	0.246	0.430	0
$\mathbb{1}\{$Lead underwritten by Barclays$\}$	3,237	0.212	0.409	0
$\mathbb{1}\{$Lead underwritten by Morgan Stanley$\}$	3,237	0.197	0.398	0
$\mathbb{1}\{$Lead underwritten by Goldman Sachs$\}$	3,237	0.147	0.355	0
$\mathbb{1}\{$Lead underwritten by Wells Fargo$\}$	3,237	0.116	0.320	0
$\mathbb{1}\{$Lead underwritten by Deutsche bank$\}$	3,237	0.136	0.343	0
$\mathbb{1}\{$Lead underwritten by Bank of America$\}$	3,237	0.175	0.380	0



This figure reproduces Figure 1 using Scope 1 carbon intensity measure. This figure illustrates how price sensitivities to CO2 emission change over months since offering.

Figure A2: Price sensitivities to CO2 emission when we use Scope 1 measures



This figure reproduces Figure 1 using Scope 1+ Scope 2 + Scope 3 carbon intensity measure. This figure illustrates how price sensitivities to CO2 emission change over months since offering.

Figure A3: Price sensitivities to CO2 emission when we use Scope 1 and 2 measures

C Additional Tables

Table A11: Trucost's carbon disclosure
Table summarizes the precision levels of CO2 emission definition. Trucost documents how the reported CO2 emissions were derived and there are 32 different types in total. We assign each type to different precision level and the following table reports our classification. Precision level 1 corresponds to the most imprecise one whereas precision level 5 corresponds to the most precise one. Our classification is more granular but consistent with the one used by Aswani et al. (2023a): our level-5 precision corresponds to their type ii): directly disclosed total emissions.

Trucost's carbon disclosure	Precision
Derived from previous year	1
Estimate based on partial data disclosure in Annual Report/10-K/Financial Accounts	1
Estimate based on partial data disclosure in CDP	1
Estimate based on partial data disclosure in Environmental/CSR	1
Estimate based on partial data disclosure in personal communication	1
Estimate derived from production data	1
Estimate scaled according to company-specific data	1
Estimate used instead of disclosure - data does not cover global operations	1
Estimate used instead of disclosure - data is normalised and no aggregating factor is available	1
Estimated data	1
Value derived from data provided in Annual Report/Financial Accounts Disclosure	2
Value derived from data provided in CDP	2
Value derived from data provided in Environmental/CSR	2
Value derived from data provided in personal communication	2
Value derived from fuel use provided in Annual Report/Financial Accounts Disclosure	2
Value derived from fuel use provided in CDP	2
Value derived from fuel use provided in Environmental/CSR	2
Value derived from fuel use provided in personal communication	2
Value split from data provided in Annual Report/Financial Accounts Disclosure	3
Value split from data provided in CDP	3
Value split from data provided in Environmental/CSR	3
Value split from data provided in personal communication	3
Value summed up from data provided in Annual Report/Financial Accounts Disclosure	4
Value summed up from data provided in CDP	4
Value summed up from data provided in Environmental/CSR	4
Value summed up from data provided in personal communication	4
Data approximated from chart/graph in Annual Report/10-K/Financial Accounts	5
Data approximated from chart/graph in Environmental Report/CSR Report/Website	5
Exact Value from Annual Report/10K/Financial Accounts Disclosure	5
Exact Value from CDP	5
Exact Value from Environmental/CSR	5
Exact Value from personal communication	5